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Parameter Identification And Fault Detection For Reliable Control Of Permanent Magnet Motors

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PARAMETER IDENTIFICATION AND FAULT DETECTION FOR RELIABLE CONTROL OF PERMANENT MAGNET MOTORS

by

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DEDICATION

To my Parents

Vukosav Svetozar Progovac

Živka Miodrag Progovac, devojačko Ćirić

and to my family

Ljiljana, Stefan i Ana

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I am eternally grateful to Professor Le Yi Wang, who contributed tremendous time to my research. Without Dr. Wang's help this dissertation would not exist. Appreciation is also due to Professor George Yin, Professor Feng Lin, and Professor Caisheng Wang for their constructive comments and valuable suggestions.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1: INTRODUCTION

1.1 Problems Statement

Being able to predict dynamic behavior, in real-time of an electrical motor during normal operation, is of essential importance for motor robust control applications, condition monitoring, and diagnosis. There are many different types of electrical motors, please refer to Figure 49. Permanent magnet (PM) machines (sinusoidal and square current machines) are part of AC family of machines. High power density, high efficiency, small weight and high reliability are advantages of PM machines which makes them applicable for ground vehicle traction, and safety critical application. Today´s electrical machines are used in operations were faulty operation can cause loss of lives and high material cost. If steering wheel motor fails it will cause loss of vehicle control. If electrical pump fails in a nuclear station or on the airplane wing control it would be a catastrophe. If gun steering mechanism fails on a tank during a battle, the tank could be lost. If winding fault insulation start to fail in order to minimize further damage to motor or generator the fault must be detected as soon as possible. In order to minimize fault impact the motor control algorithm must be sufficiently adaptable so that electrical machine could continue to perform basic functions even in the presence of a major fault. Based on statistical data compiled by Electric Power Institute (EPRI) and by [61], 47% of motor failures are due to electrical faults. The 47% can be further broken down into rotor problems 10% and stator winding problems 37%.

There are many identification methods used in practice. The good on-line identification method,should be executing in real-time, should work well regardless specific conditions, i.e it should be robust. As it is well known the least-square method is not nominally robust.In this thesis we start with least-square method but with series of improvements to overall identification process which should result in improving overall method robustness. The robustness of overall proposed identification and fault detection procedures will be built upon

- optimal continuous system discretization
- application of least-square identification recursive method
- introducing algorithm for bias removal
- robust filtering approach to remove non-modeled dynamics
- robust test design
- robust outliers detection and removal
- robust fault detection

1.2 Objective And Motivation

The objective of this dissertation is to develop robust algorithm for fault detection, identification and control of electrical motors. Developed algorithms will be used to detect winding stator fault, identify the motor parameters and optimally control permanent magnet machines during faulty condition. Quality of proposed algorithms for parameter identification, fault detection and control under faulty condition will be validated through simulation. Simulation will be performed for three most applied control schemes: Proportional-Integral-Derivative (PID) control, Direct Torque Control (DTC) and Field Oriented Control (FOC) for Permanent Magnet Machines. New detection schemes for fault detection, isolation and machine parameter identification will be presented and analyzed.

1.3 Literature Review

This subsection presents comprehensive review on existing methodologies in the field of fault detection, system identification, parameter estimation and fault tolerant control for permanent magnet electric machines.

This thesis is about robust parameter identification of continuous systems (permanent magnet motors) through sampling, detection of single system fault (winding fault) and fault tolerant control of permanent magnet motor in the case of a fault existence.

According to Norton, [77], identification is the process of constructing a mathematical model of a dynamical system from observation and prior knowledge. The knowledge of mathematical model allows for estimating what plant dynamics would be if certain inputs to plant are presented. For that reason many control algorithms assume knowledge and use of plant mathematical model. The other area where model identification is in usage is fault detection. The parameter identification starts upon the plant model is constructed in some way. How to construct an optimal plant model for identification is a complex problem which depends on type of design: control, fault detection, type of the plant, etc. The good match of model to plant dynamics is necessary for successful identification or fault detection. Some prominent works which study identification dependance on how well plant model matches plant dynamics are done by [37, 38].

Today there are many identification methods: least-squares,total squares, instrumental variables, subspace identification, non-linear identification methods etc. Each method has its own advantages and disadvantages in identification speed of convergence, robustness to noise characteristics in input and output signal measurements, plant parameter variation and complexity of the method itself. Which method is selected as optimal is based on concrete case and requirements. The least-square methods could be deterministic or stochastic and it is the oldest and most applied identification method despite some known weaknesses. The first publication on least-square was by Legendre in 1805, although Gauss claimed in 1809 that he discovered it much earlier and that he had been already applying it in his research since 1795. For a paper discussing origin of least squares please see [100].// It is known that least-square provides for non-biased estimation if only noise is present at the output of a plant. Existence of noise in the measured plant input data may produces biased estimates. Some other identification methods, as for example total squares or instrumental methods, are much more resistant to both input and output noise signal measurement, see [44], [95], [96], [97] but these methods are more complicated and its accuracy is achieved only if full knowledge of noise statistics is available. On the other hand speed of the least-square method allows for real-time applications which is necessary for any real-time application.There are many attempts in practice to eliminate bias of the least-squares method for so called error-in-variables case, i.e the case when input signal noise is correlated with output noise. The correlation between noise at input and output of the plant is predominant in engineering applications. In industrial feedback situations the noise at input and plant output are correlated due to feedback loop. In early 60's the measurement noise was assumed gaussian due to fact that measurements of input and output of the plant were considered non interacting mostly due the fact that feedback loop was analog. That approach lead to Kalman filter and successful application of control algorithms in space flight area. Today many power supply system, for on board electronics, are impulsive in the nature with digital feedback loop so therefore in many cases assumption about gaussian noise nature can't be justified. In this thesis least-square bias removal algorithm is based on methods originally proposed and developed by L.Y. Wang and coworkers, [94]. For alternative approaches in literature please see, for example, [118], [117].

Problem of improving identification algorithm robustness could further be approached by optimizing each components of the whole identification process: plant modeling (which comes prior to identification), optimizing continuous model discretization, optimizing sampling speed with regards to identification, inclusion of a priori knowledge into identification algorithm and using statistical decision theory for finding the most powerful hypothesis testing scheme[42], [43], [106].

Modeling of invertor driven electrical motors for identification presents a challenge for current identification methods and practices. Input signal, the voltage, is essentially square-wave signal of fixed amplitude with pulse width control so that phase currents follow required patterns. The modulation process is known under name of Pulse Width Modulation (PWM). For parameter identification prior to identification process, the plant model is discretized and then data is collected through sampling plant inputs and outputs. A technical difficulty at that point is to determine required Nyquist sampling speed based on Kotelnik-Shannon theorem. In the literature it has been shown that required sampling speed should be determined so that sampling zeros do not negatively influence identification resolution, [115, 28, 31, 93, 17].

Effective fault detection algorithm design for an invertor driven electrical motors is an important and difficult applied engineering and reliability topic. Different approaches to modeling stator fault are given in papers [1, 26, 52, 62, 63, 88, 105]. Fault detection algorithms do detect fault by estimating size of so called fault residues. For electrical motors residues could be based on sensing some signals, or, using different forms of observer design for estimating fault residues. In this thesis proposed methods detect fault based on identification methods, exploiting built-in symmetry of winding phases and using detection theory to make decision about fault presence. In the last step for winding fault detection the hypothesis testing is introduced by proposing two different robust tests. Hypothesis testing is used everywhere: finance, military, science, engineering, etc. Several crucial moments in theory development were Nyquist-Pearson proposal of likelihood test, A. Wald contribution during Second World War and work of P.J. Huber and the others from 60´s to today in the area of robust statistics. Neyman-Pearson proposed lemma in 1928 which now has their name . This lemma claims that the most powerful test for deciding between two simple hypothesis, if sample size is fixed, is likelihood ratio test. At that time statistics of hypothesis was considered fully known. A decade later A. Wald was working during Second World War with goal to determine what shortest time is necessary to detect right hypothesis with proposed risk. Although sequential statistical methods were known for some time before A. Wald, they were only simple or ad-hoc rules. His result were further generalized by A. Shiryaev in 60´s. Until P.J. Huber work in mid sixties, [42], the statistics of hypothesis was assume to be Gaussian.

In mid 60´s statisticians got alarmed with many wrong conclusions based on assumption that distributions were normal when in reality there were only close to Gaussian. Huber introduced homotopy mechanism, see [42], in order to control 'distance' between distributions. For more information Huber´s original book, [43], is a good source. There are several books published so far covering the robustness in statistics by P.J. Huber, F.R. Hampel, P.J. Rousseeuw, R.A. Maronna. For published papers, on which this this thesis is based, please see [83],[84] and [85].

1.4 Originality and Contributions

The main contributions of this thesis are in the following aspects. (1)Thesis establishes the robust identification method based on building robustness of individual identification components: plant model design, plant model discretization, bias removal, outlier detection & elimination and application of hypothesis testing. (2) Designing robust identification method executing in real-time and therefore applicable for industrial real-time safety application and in econometrics for real-time market dynamics identification. (3) For practical application and validation the identification method is applied on important practical problem by itself: permanent magnet motor parameter and fault identification. (4) In modeling linear permanent magnet model motor new, original results were achieved in developing closed expression for estimation of fault current. (5) New nonlinear permanent magnet motor model is presented which allows for saturation and saliency modeling (6) Original detection and outliers elimination is presented with benefit of increased identification accuracy being achieved. (7) The new role of filtration is proposed: in instrumental variable method filtration is used only to eliminate noise whereas in this thesis the proposal is to use filtration not only to limit information loss due to present noise but also to eliminate influence of the model dynamics which, for some design reason, should be ignored and not involved in identification.

1.5 Thesis Overview

The thesis is organized into the following sections. Section 2 presents physical motor architecture, type of input control signal as well as discussion of the input and modeling noise. In the rest of this section most often control scheme used were briefly discussed. As it is known for long time the plant identification in closed loop poses new challenges. For that reason identification simulation results are obtained from three different Simulink closed loop models whose details are given in this section. Section 3 presents plant continuous model which in this case are two types of permanent magnet motor: motor with sinusoidal back electromotive force (back-emf) and with trapezoidal back-emf. The most often alias names for these motors in practice are permanent magnet synchronous motor, PMSM, and brushless DC motor, BLDC. In the same section the linear continuous model of the motor width winding fault is presented. Section 4 presents universal model for permanent magnet motor by including effects of saturation and saliency. In the literature there are many different proposed ways how to introduce non-linear effects into permanent magnet lumped modeling but all proposed methods are based on ad-hoc assumptions justifying only effects observed but not model itself. The presented original model has been designed with several goals in mind. The first goal was to have general model whose approximation error could be controlled.This was achieved by controlling number of terms of Fourier expansion. The second goal was to avoid ad-hoc assumption but also to design model convenient for identification approach. The Fourier approach does satisfy that goal because it can be used for any static nonlinearity. Section 5 discusses ways to discretize linear continuous model so that resultant discrete model be as close as required approximation of continuous plant. Relative results regarding sampling zeros from literature are used in order to build and justify robust identification approach. Section 6 goes over least-square identification method details when that method is applied to permanent magnet identification. Section 7 shows how least-square method could be made robust and non-sensitive to input noise correlation through bias removal and outliers detection. Section 8 discusses abrupt change detection methods relevant for winding fault detection. Basic assumption for fault detection algorithm is that at any time only one winding fault exists. This may be quite logical assumption because fault detection process start from healthy motor. The winding fault detection importance, treated in this thesis, it is based on General Electric's published studies in 60's showing that approximately half of faults on electrical motors are winding faults. Section 9 presents way for fault tolerant control of electric motors. Section 10 presents the motor plants used during this study.

CHAPTER 2: BACKGROUND

2.1 PM Motor Architecture Assumed in this Thesis

Typically in engineering, built-in physical redundancy is used to enhance plant robustness and reliability [69, 65]. Figure 1 represents a commonly accepted robust motor and inverter architecture that includes hardware redundancy: additional converter leg on the right side of the figure and the additional wire to neutral point. Assuming this configuration, we assume from now on that the neutral point (point O in the figure) is available for voltage control. Although many PM motors of lower grades do not have fourth wire connection, for high-reliability monitoring and fault detection, this added feature provides additional necessary freedom in loading phase voltages and, as it will be shown latter, it will allow generation of Tesla rotating field even with only two working stator windings.

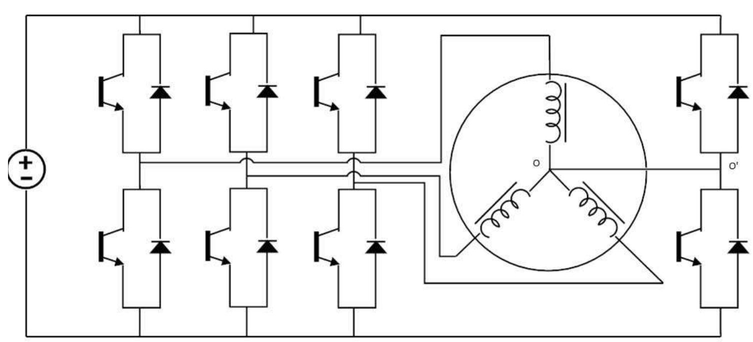


Figure 1: Robust inverter and motor architecture

An partially effective approach for winding fault detection, currently used in industry, is to insert thermal sensors inside stator windings.Finite element thermal analysis is then applied to estimate normal temperature distribution. Then, based on comparing temperature measurements and predicted temperature ranges a winding fault can be detected. However, this configuration is very costly, it used only in very selective systems such as missiles or airplanes where system safety overwrites system costs. The other weakness of the method is that fault detection is usually late: only after considerable insulation damage, when the motor is already heavily damaged, the temperature may rise enough for sensor to sense it. In majority cases temperature sensorless approach would cost less, and hence be preferred. However currently available sensorless fault detection algorithms had only limited success [52, 51, 65, 19]. The poor performance of sensorless approach is mostly due to algorithm deteriorated performance when measurement data are highly noise corrupted or parameter value changes due to temperature or age. In converter-based systems in which the voltage motor inputs are switched the high impulse noise factor is especially a severe drawback either for system identification or fault detection . The other difficulty of applying fault detection algorithms universally is the fact that there are many different types of electrical motors, please see Figure 49. The algorithms for fault detection in this thesis should be effective for all types of the motors having similar stator winding design. It is assumed although that a specific correction to algorithm could be required if motor rotor construction is significantly different. For example, stator motor construction is arguably the same for Induction Motor and Permanent Magnet Motor but fault detection and control schemes are different due to different rotor construction.

2.2 Input Signal Model

Motor torque and speed are controlled by changing phase´s voltage amplitude and frequency. Changing amplitude of phase voltage could be done through linear amplification but level of input motor currents are high and therefore the losses of such amplifier would be high. In practice both change of phase voltage amplitude and frequency is done using inverters and pulse width modulation (PWM).

The simplified form of converter-inverter is shown on Figure 2. It is essentially composed from three functionally different blocks: converter, capacitor as energy storage and inverter block. The middle block is relatively big capacitor which is a storage for DC electrostatic energy pumped in by converter block. Both converter and inverter are composed from six IGBTs (Insulated Gate Bipolar Transistors) arranged in two levels. The converter block function is to rectify AC input signal into DC signal which energy is then going to be stored into capacitor. Each IGBT, in converter or inverter block, is working as a switch with ON-OFF state.This way heating losses are much less then if linear amplification is used because ON state is a saturation state with very small resistance.

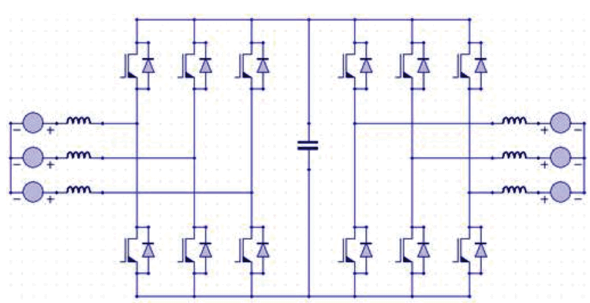


Figure 2: Two-level three-phase converter-inverter with voltage DC-link

Inverter high level schematic where IGBTs are replaced with switches is presented on Figure 3. Please note that by changing switching frequency of inverter IGBTs the signal of any fundamental frequency can be produced. Simple example is presented on Figure 4.

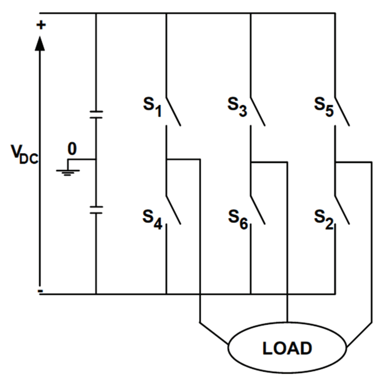


Figure 3: Two-level inverter functional representation

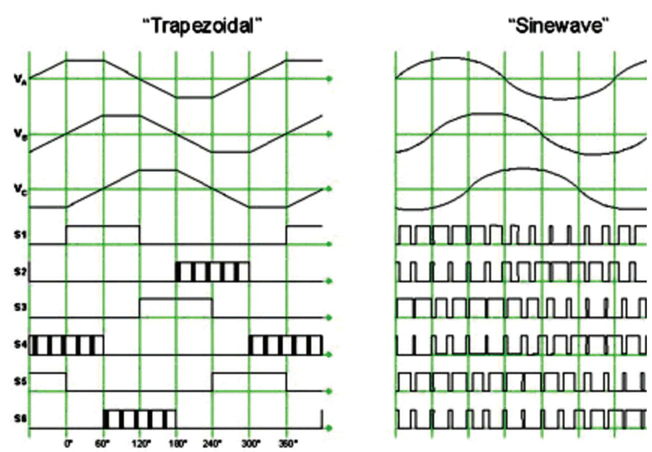


Figure 4: Inverter approximation of trapezoidal and sinusoidal voltages

On Figure 5 the measurement of currents of three-phase mid-size motor are given. As it can be seen these waveforms are required sinusoids with a lot of additional harmonics and high frequency noise. Please note that high-level harmonics and noise presence makes any identification of the motor parameters very hard and challenging.

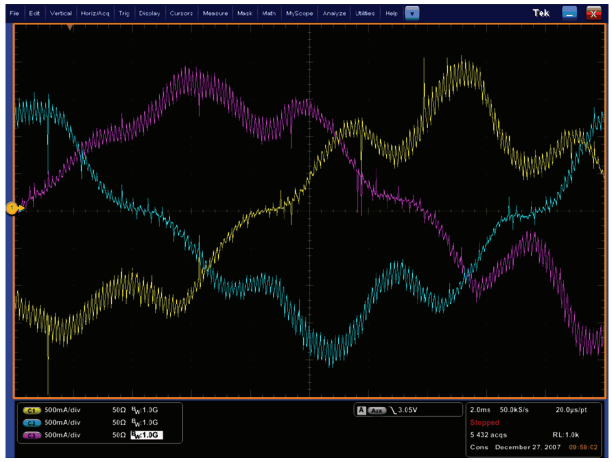


Figure 5: Phase currents for sinusoidal motor powered by 3-phase inverter

As noted above the inverter switches are closed in required succession to produce sinusoidal currents in stator windings which are conventionally called, in the case of three phase motor, as phases a, b and c. The current in each phase produces magnetic field. The magnetic field from individual phases add and produce resultant space field around motor rotor. The resultant field will be Tesla rotating field if phase currents are sinusoidal of the same frequency, phases are spaced for 120° and time shift between these frequencies is again 120°.

Geometrically the inverter supplying healthy three phase motor can produce only six magnetic vectors, see Figure 6. In the case one of phases is out due to winging fault it is a challenge to produce six magnetic vectors which are sufficient to produce relatively smooth motor rotation. Latter it will be shown how that can be done if inverter and motor are of type given on Figure 1.

Explantation given above are for sinusoidally operated permanent magnet motor. For brushless DC motor (BLDC) the rotation magnetic field is not exactly rotating magnetic field but its sampled form. In the case of BLDC motor using inverter we are producing

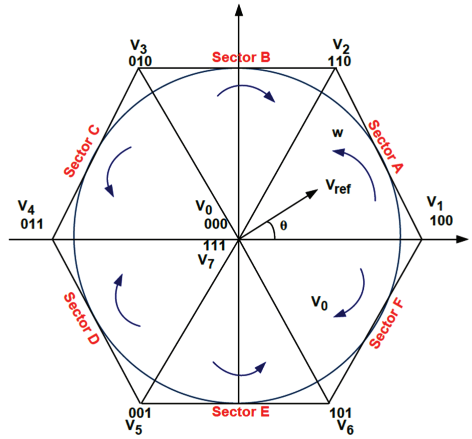


Figure 6: Space vector diagram for two-level inverter

approximation of theoretically required signals, see Figure 7.

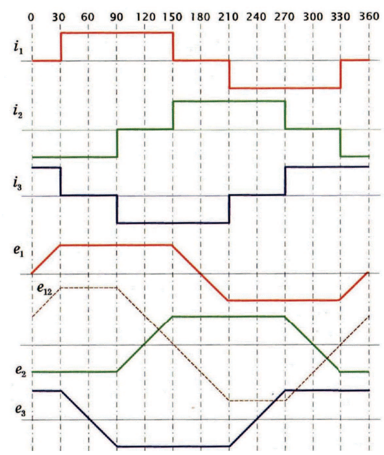


Figure 7: Idealistic BLDC motor phase variables

An example of signals collected on a real motor, are given on Figure 8.

2.3 Plant Modeling

We always built plant model for identification based on some optimality criteria. Implicitly the model approximation of plant is always over some range of frequency or time. So in

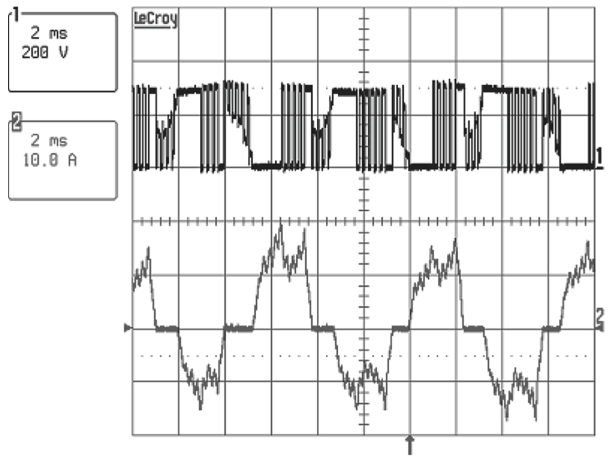


Figure 8: Measured BLDC voltage and current

practice we always work with constraint identification problem as the constraints are tacitly assumed. On the other hand, for control purposes, we very often intentionally use simplified plant models and sometimes no models at all as in the case of bang-bang control. So the goal of identification is to identify plant as close as possible to the required control model but neither worse or better than that. Geometrically we can say that we are looking to project plant on our model space (the model which we will use to identify parameters of the plant). Electrical motors are usually energized from voltage inverter and the basic parameters like resistance, self and mutual inductance should be identified with relatively high precision as long as the discrete model is 'close' to plant model. Please note that some averaging is not only allowed but also wanted because instantaneous values of currents could be caused by poles of the plant we do not want to identify. In engineering we always start from simple linear model and then, as perturbation, the other important phenomena are included. In the literature, nearly exclusively, only linear models are presented for electrical models. Here we extend these models by including two main nonlinear effects.

2.4 Relation between Identification and Control

We introduce now new methods for accurate parameter estimation and reliable fault detection with inverter powered electric motors. In this thesis BLDC and PMAC motors are used as a benchmark platform to develop and validate our methods. The reason for using BLDC and PMAC for study is that these kind of electric motors are essential parts of electric and hybrid vehicle powertrains and other diversified industrial applications [34]. Accurate model identification and fault detection are necessary for reliable motor control [20]. Motor-characterizing parameters experience substantial changes or sudden jumps due to temperature, aging, motor operating conditions, and faults [29]. Consequently, motor parameters must be estimated accurately during operation, leading to a system identification problem [95, 71].

Here 3-phase motors are used as a platform to develop algorithms for identifying motor parameters during normal operations and detecting stator winding faults. To facilitate this study, an enhanced model of 3-phase PM motors is developed that accommodates both normal and faulty operating conditions. The model allows us to use the imbalance caused by inter-turn faults to derive a reliable diagnosis algorithm. Due to high measurement noise, motor parameter estimation is a challenging problem. Both motor inputs and outputs are measured and corrupted by noise. This system structure creates a more difficult identification problem termed as "errors-in-variables identification (EIV) problem" [95]. An EIV structure is known to introduce identification bias [98]. Motor faults may cause sudden jumps or other forms of uncontrolled form of motor dynamics. To diagnose the faults promptly, identification algorithms must achieve a good balance between fast fault detection (which prefers a short data window), and noise attenuation (which is achieved by averaging, preferably over a large data window). Also, motor controller frameworks are pre-designed and must be accommodated in system identification.

The identification will be based on proposed enhanced LS (least-squares) estimation algorithm that incorporates a bias removal function for correcting estimation bias, a forgetting factor for capturing sudden faults, and a recursive structure for efficient real-time implementation. Algorithms are presented, their properties are established, and their accuracy and robustness are evaluated by simulation case studies under both normal operations and inter-turn winding faults. One key contribution of this thesis is the development of new bias correction algorithms with forgetting factors in a recursive structure. Traditionally, bias correction in an EIV problem was treated by modified correction terms, instrumental methods, or prediction error methods [95, 97, 41]. In an earlier paper [94], a LS-type recursive bias correction algorithm was developed for battery model identification. In the other earlier paper, Dr. Wang and coworkers used a two-time-scale approach to reduce bias in joint SOC and parameter estimation in [94]. However, recursive algorithms for bias correction with forgetting factors are new.

The rest of this thesis is organized into the following sections. Section 3 establishes enhanced model structures for three-phase balanced PM motors in normal and faulty conditions. Identification algorithms are introduced in Section 6. In Section 7, bias-corrected LS algorithms are presented and their bias correction capabilities are established. Section 7.9 discusses practical aspects of motor estimation, involving different motor control schemes. Reliability of parameter estimation under these schemes is studied. For fast diagnosis of faults, system identification must balance speed and accuracy. Section 7.10 introduces forgetting factors into our bias correction algorithms. Recursive algorithms are derived. Section 9 concentrates on inter-turn fault diagnosis. Basic algorithms are introduced and evaluated by case studies. Section 11 highlights the main findings of this thesis and points out some worthy open problems. Some preliminary ideas of this paper were reported in [83].

2.5 PM Motor Control

PM motors are usually operated in a closed loop setting. Depending on detection methods, the fault diagnosis reliability depends on the closed-loop characteristics. For AC motor control, three dominant approaches for closed loop design are: Proportional-Integral-Differential (PID), Field Oriented Control (FOC) and Direct Torque Control (DTC). For these designs the machine torque is expressed as the product of rotor and stator fluxes. In the case of FOC the rotor flux is kept constant and stator flux is expressed through the stator current. In this case, the stator current control is accomplished by two current loops, see Figure 9.

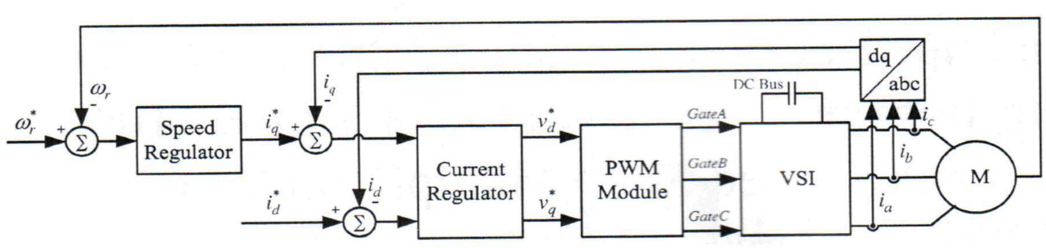


Figure 9: Simplified diagram for a closed-loop motor drive control

The FOC method requires the exact knowledge of machine parameters so it may become less satisfactory when model parameters are only estimated. The DTC approach is based on 'time decoupling'. It is known that DTC dependence on machine parameters is minimal: We need to know only the stator resistance (not true for FOC). Two DTC flavored methods were developed in the mid 80´s: The circle approach by Takahashi and Noguchi and the hexagon approach by Depenbrock. Although for nominal torque control these two approaches are equivalent, during a stator fault, they offer different flexibility in control. Figure 10 shows Depenbrock´s approach.

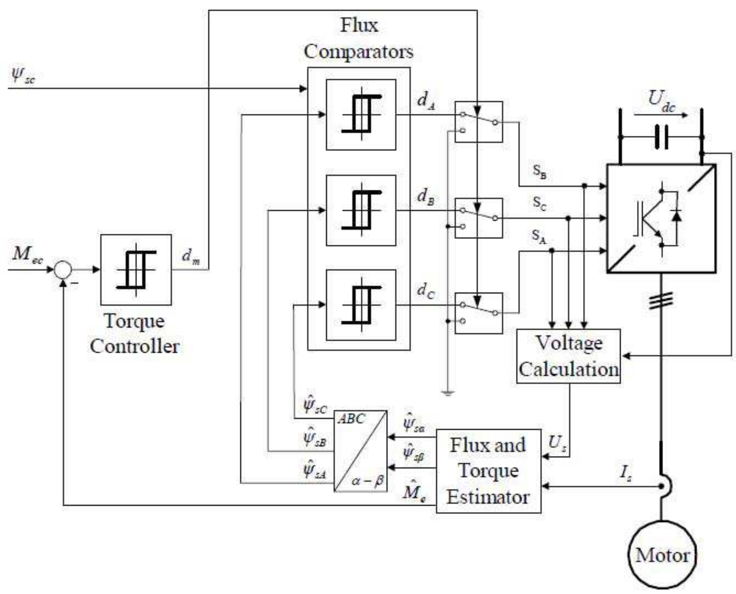


Figure 10: Depenbrock´s DTC: Direct Self Control Method

There are two types of PM drives: sinusoidal feed and constant current feed. The sinusoidal PM drives may be equipped with either a surface laid magnet and an inserted magnet in the rotor core. From the modeling point of view, the surface magnet drives are non-salient. The main reason for inserted magnets is to get saliency or obtain higher concentration of magnetic field. From the winding point of view, sinusoidal fed drives have sinusoidally distributed windings and constant current drives have concentrated windings.

Sinusoidally distributed windings result in sinusoidal induced electromotive forces. In the case of concentrating windings the induced electromotive force is trapezoidal. There is one crucial difference between sinusoidal and rectangular fed drives. In sinusoidal three phase drives all three phase windings conduct current simultaneously. On the other hand BLDC drives dominantly have only two windings active at any time.

In this thesis, in consideration that the most elementary permanent magnet drives are surface mount sinusoidal drives, we will focus on their models in developing our system identification algorithms. Extension to other driver types does not impose additional technical difficulties. For winding fault model, we will use one contained in [1, 26, 74, 88].

For identification data collection and validation simulation of three closed loop models (Six-Step, FOC and Self-Controlled) were used together with two different motor models (continuous and discrete). Each simulation trial starts with model representing a healthy motor and then, usually at 2s, the model is switched to a motor with one faulty winding. The level of fault was modeled by number of windings involved in the fault and level of insulation damage. Also, each motor model was able to simulate concentrated or sinusoidally distributed stator windings. Noise was possible to inject both into input (input phase voltage and back EMF) and output(stator currents) measurements.

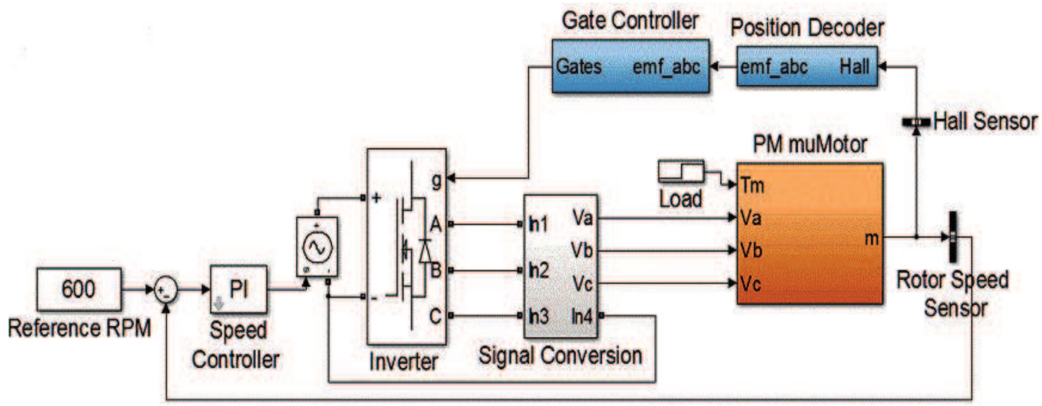


Figure 11: Six-Step Controlled PM Motor

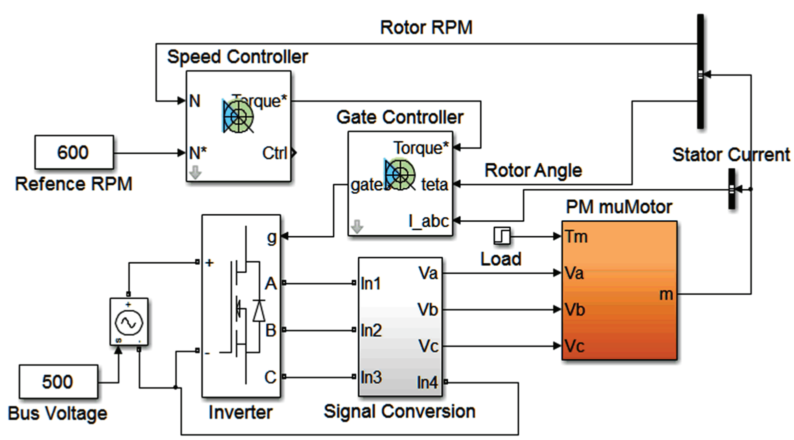


Figure 12: FOC Controlled PM Motor

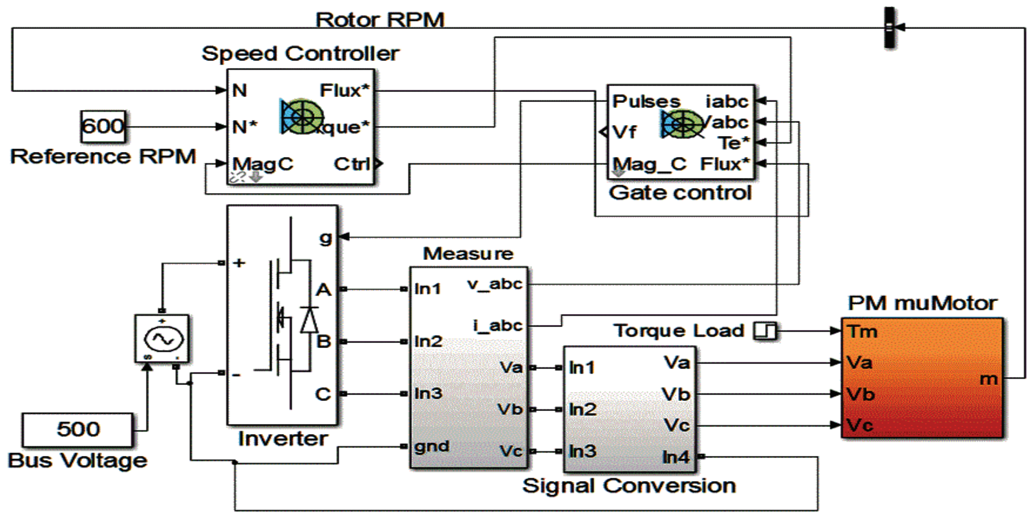


Figure 13: Self Controlled PM Motor

2.6 BLDC Two-Windings Control Method

One of the goals of the thesis is also to present method for motor control in the case if winding fault exists. If one of windings can not be used for rotating field generation then two remaining windings should be sufficient for rotating field generation with reduced torque, please see 9 because two independent vector span whole rotation plane. For PM motors,in literature, only orthogonal two windings for production of rotating field are considered. In BLDC case the windings are under 120 degrees what will place limitations on control and flux weakening. Also current lead angle should be changed to 180 from 120 degrees if the rotating field to be produced with two phases.

CHAPTER 3: LINEAR CONTINUOUS PM MOTOR MODEL

3.1 Linear PM Healthy Motor Model

This section describes linear models of surface mounted PM motors. For working principles, types, mechanisms, and control systems of PM motors, reader can refer to [34, 29] for details. Exploration on modeling and diagnosis of surface mounted PM machines can be found in [20, 7, 88, 9, 78]. In this paper, we introduce an enhanced model for PM motors in normal and faulty conditions. The three-phase balanced stator windings under normal operating conditions are illustrated in Figure 14 . Under a balanced construction, all phases have the same parameters and are symmetric.

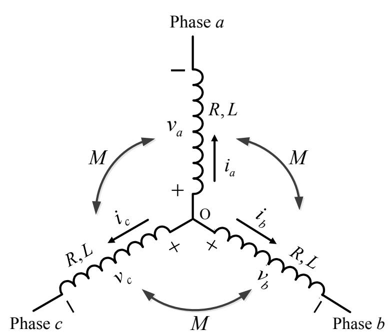


Figure 14: Electromagnetic model for healthy three-phase stator winding

We start with models of healthy stator windings; see Figure 14, in which the windings are assumed to be sinusoidally distributed.[1] Since the stator windings are balanced, without loss of generality, we use Phase a as a generic phase. The state equation for healthy stator

[1] It should be emphasized that the model structures are also valid under other types of flux linkages and back emf (electromotive force), such as trapezoidal types.

windings is

$$v_a = Ri_a + \frac{d\lambda_a}{dt}, \tag{3.1}$$

where v_a is the phase-a winding terminal voltage (V), i_a is the phase-a current (A), R is the phase-a resistance (Ω), and λ_a is the total phase-a flux linkage (Wb). Under the assumption of magnetic linearity and infinite permeability of iron, the flux linkage is related to the phase current and magnetic coupling by $\lambda_a = Li_a + Mi_b + Mi_c + \lambda_M \cos(2\pi f t + \delta_a)$. Here, L is the phase-a inductance (H), M is the stator phase cross-inductance (H), λ_M is the stator/rotor magnetic coupling flux linkage (Wb), f is the electric angular speed of the rotor (Hz), and typically $\delta_a = 0$ (rad) ($\delta_b = -2\pi/3$ and $\delta_c = 2\pi/3$).

Assume that there is no saliency, i.e., the air gap between the rotor and the stator is constant. Then the stator inductance is constant and does not depend on the relative rotor position. It follows from (3.1) that

$$v_a = Ri_a + L\frac{di_a}{dt} + M\frac{di_b}{dt} + M\frac{di_c}{dt} - \lambda_M 2\pi f \sin(2\pi f t + \delta_a). \tag{3.2}$$

This can be written compactly as

$$v(t) = RIi(t) + H\frac{di(t)}{dt} + \lambda_M g(t) \tag{3.3}$$

where $v(t) = [v_a(t), v_b(t), v_c(t)]'$, $i(t) = [i_a(t), i_b(t), i_c(t)]'$, $H = \begin{bmatrix} L & M & M \\ M & L & M \\ M & M & L \end{bmatrix}$, $g(t) = [g_a(t), g_b(t), g_c(t)]'$ with $g_a(t) = -2\pi f \sin(2\pi f t + \delta_a)$, $g_b(t) = -2\pi f \sin(2\pi f t + \delta_b)$, $g_c(t) = -2\pi f \sin(2\pi f t + \delta_c)$.

3.2 Continuous Linear PM Motor with Stator Winding Fault

Within this frame, when the stator is subject to a winding fault, the model (3.3) is perturbed. We will use the phase-a fault as a benchmark case in our derivations, see Fig.

15. Detection algorithms for phase-b and phase-c faults are similar.

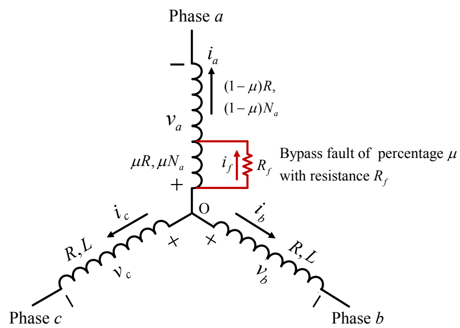


Figure 15: Three phase stator windings with a bypass fault in phase a

Suppose that the original number of turns of Phase a is N_a for which N_{as} turns are shorted. Denote $\mu = N_{as}/N_a$, the ratio of faulty turns. It is noted that the fault introduces a fault current i_f through the bypass branch of resistance R_f in Fig. 15. Fault diagnosis is built on the following enhanced model which captures inter-turn faults with bypass resistance. Here, we assume that the healthy motor model has been identified with model parameters R, L, M, λ_M estimated. Fault detection aims to identify additional parameters that represent inter-turn faults. From Fig. 15, such parameters include μ and R_f.

Following the same principles as before, under a fault of $0 < \mu < 1$ in Phase a with resistance R_f, the model (3.3) is perturbed to

$$\begin{aligned}
v_a &= v_f + (1-\mu)Ri_a + \frac{d}{dt}((1-\mu)^2 Li_a + (1-\mu)\mu L(i_a - i_f) \\
&\quad +(1-\mu)Mi_b + (1-\mu)Mi_c) + (1-\mu)e_a \\
v_f &= \mu R(i_a - i_f) + \frac{d}{dt}(\mu(1-\mu)Li_a + \mu^2 L(i_a - i_f) + \mu Mi_b \\
&\quad +\mu Mi_c) + \mu e_a \\
v_b &= Ri_b + \frac{d}{dt}((1-\mu)Mi_a + \mu M(i_a - i_f) + Li_b + Mi_c) + e_b \\
v_c &= Ri_c + \frac{d}{dt}((1-\mu)Mi_a + \mu M(i_a - i_f) + Mi_b + Li_c) + e_c \\
v_f &= R_f i_f,
\end{aligned}$$

where v_f is the voltage cross the faulty turns. By eliminating v_f, we obtain

$$\begin{aligned}
v_a &= Ri_a - \mu Ri_f + \frac{d}{dt}(Li_a + Mi_b + Mi_c - \mu Li_f) + e_a \\
v_b &= Ri_b + \frac{d}{dt}(Mi_a + Li_b + Mi_c - \mu Mi_f) + e_b \\
v_c &= Ri_c + \frac{d}{dt}(Mi_a + Mi_b + Li_c - \mu Mi_f) + e_c \\
R_f i_f &= \mu R(i_a - i_f) + \frac{d}{dt}(\mu Li_a + \mu Mi_b + \mu Mi_c - \mu^2 Li_f) \\
&\quad +\mu e_a.
\end{aligned} \tag{3.4}$$

The first equation implies

$$\mu v_a = \mu Ri_a - \mu^2 Ri_f + \frac{d}{dt}(\mu Li_a + \mu Mi_b + \mu Mi_c - \mu^2 Li_f) + \mu e_a$$

which, after substituting into the fourth equation, leads to

$$i_f = \frac{\mu}{R_f + \mu R - \mu^2 R} v_a, \;\; v_f = \frac{\mu R_f}{R_f + \mu R - \mu^2 R} v_a. \tag{3.5}$$

It is interesting to note that this relationship between v_f and v_a is independent of the value L.

It follows that $\mu i_f = \frac{\mu^2}{R_f + \mu R - \mu^2 R} v_a = \kappa v_a$ where

$$\kappa = \frac{\mu^2}{R_f + \mu R - \mu^2 R}. \tag{3.6}$$

Now, using (3.6) to eliminate i_f in the first three equations in (3.4) results in

$$\begin{aligned}
v_a &= Ri_a - \kappa R v_a + \frac{d}{dt}(Li_a + Mi_b + Mi_c - \kappa L v_a) + e_a \\
v_b &= Ri_b + \frac{d}{dt}(Mi_a + Li_b + Mi_c - \kappa M v_a) + e_b \\
v_c &= Ri_c + \frac{d}{dt}(Mi_a + Mi_b + Li_c - \kappa M v_a) + e_c.
\end{aligned}$$

These can be compactly expressed as

$$v = RIi - \kappa G_1 v_a + H\frac{di}{dt} - \kappa G_2 \frac{dv_a}{dt} + g \tag{3.7}$$

where H and g are defined before, and $G_1 = (R, 0, 0)'$, $G_2 = (L, M, M)'$.

CHAPTER 4: NONLINEAR CONTINOUS PM MOTOR MODEL

There are two main causes of nonlinearities in electrical motor magnetic field

1. motor magnetic saturation

2. motor magnetic saliency

So far it was assumed that modeling linear effects is sufficient for modeling electrical motor. Although for some motors, like permanent magnet surface mounted motors, that is arguably good approximation there are motors where nonlinearity levels are mich higher. Nonlinear effects are 'space' phenomena and these can't be described using lumped circuit approach. Usually, in the literature, for dependance between current i and magnetic inductance $L = L(i)$ some nonlinear function is proposed based on practical experience that these kind of approximations are close to observed manifestation in real-life situation where saturation is present. Some authors suggest dependency between current and inductance to be a tangent law $\text{tang}(i)$, other propose polynomial approximation, etc.

Linear motor models are lumped representation of space phenomena where interaction of electrical and magnetic fields are reduced to lumped approximations using superposition. Lumped model can only represent 'point' phenomena and not distributed one. On the other hand the level of saturation and so non-linearity, for example, changes from point to a point in the core. In our previously presented model only time but not time coordinate is present. There is common understanding, based on measurements, that saturation and saliency nonlinearities influence harmonics in air-gap magnetic field. In some papers for modeling saturation only third harmonic is considered as existing. Here we consider the influence of both saliency and saturation so we consider existence of 2nd and 3rd harmonic for stator magnetic field and only first harmonic for representation of rotor magnetic field. The proposed model complexity is arguably an improvement on currently available models in the literature.

4.1 Healthy Non-Linear Continuous Motor Model

The goal here is to have approximate mathematical model for both saliency and saturation effects observed in practice. Regardless of non-linearity $L = L(i)$ assumed, Fourier expansion may be used

$$L_{aa} = L + \mathrm{l}_g \cos(2n_g\theta)$$

$$L_{bb} = L + \mathrm{l}_g \cos(2n_g\theta + \tfrac{2\pi}{3})$$

$$L_{cc} = L + \mathrm{l}_g \cos(2n_g\theta - \tfrac{2\pi}{3})$$

$$L_{ab} = M + m_g \cos(2n_g\theta - \tfrac{2\pi}{3})$$

$$L_{bc} = M + m_g \cos(2n_g\theta)$$

$$L_{ac} = M + m_g \cos(2n_g\theta + \tfrac{2\pi}{3})$$

where θ is rotor mechanical angle n_g is number of pole pairs on the stator L is

self-inductance M is mutual inductance

For rotor magnetic coupling to stator we assume existence of first and third harmonic only.

$$\Phi_{ra} = \sum_{i=1,3} \psi_{ri} \cos(n_g i\theta) = \psi_{r1} \cos(n_g\theta) + \psi_{r2} \cos(3n_g\theta)$$

$$\Phi_{rb} = \sum_{i=1,3} \psi_{ri} \cos(n_g i\theta - \tfrac{2\pi}{3}) = \psi_{r1} \cos(n_g\theta - \tfrac{2\pi}{3}) + \psi_{r2} \cos(3n_g\theta - \tfrac{2\pi}{3})$$

$$\Phi_{rc} = \sum_{i=1,3} \psi_{ri} \cos(n_g i\theta + \tfrac{2\pi}{3}) = \psi_{r1} \cos(n_g\theta + \tfrac{2\pi}{3}) + \psi_{r2} \cos(3n_g\theta + \tfrac{2\pi}{3})$$

The permanent magnet motor is

$$v_s = Ri_s + \tfrac{d\Phi_s}{dt}$$

$$v_s = \begin{bmatrix} v_a \\ v_b \\ vc \end{bmatrix}; \Phi_s = \begin{bmatrix} \Phi_a \\ \Phi_b \\ \Phi c \end{bmatrix}; i_s = \begin{bmatrix} i_a \\ i_b \\ ic \end{bmatrix};$$

where

R phase resistance Φ_s stator total flux v_s stator voltage i_s stator current

$v_a = R_a i_a + \frac{di_a}{dt} L_{aa} + \frac{di_b}{dt} L_{ab} + \frac{di_c}{dt} L_{ac} + \omega(i_a \frac{\partial L_{aa}}{\partial\theta} + i_b \frac{\partial L_{ab}}{\partial\theta} + i_c \frac{\partial L_{ac}}{\partial\theta}) - \psi_{r1} n_g \omega \sin(n_g\theta) - 3\psi_{r1} n_g \omega \sin(3n_g\theta)$

$v_b = R_b i_b + \frac{di_a}{dt} L_{ba} + \frac{di_b}{dt} L_{bb} + \frac{di_c}{dt} L_{bc} + \omega(i_a \frac{\partial L_{ba}}{\partial\theta} + i_b \frac{\partial L_{bb}}{\partial\theta} + i_c \frac{\partial L_{bc}}{\partial\theta}) - \psi_{r1} n_g \omega \sin(n_g\theta - \frac{2\pi}{3}) - 3\psi_{r1} n_g \omega \sin(3n_g\theta - \frac{2\pi}{3})$

$v_c = R_c i_c + \frac{di_a}{dt} L_{ca} + \frac{di_b}{dt} L_{cb} + \frac{di_c}{dt} L_{cc} + \omega(i_a \frac{\partial L_{ca}}{\partial\theta} + i_b \frac{\partial L_{cb}}{\partial\theta} + i_c \frac{\partial L_{cc}}{\partial\theta}) - \psi_{r1} n_g \omega \sin(n_g\theta + \frac{2\pi}{3}) - 3\psi_{r1} n_g \omega \sin(3n_g\theta + \frac{2\pi}{3})$

The canonical form is

$\frac{di_a}{dt} L_{aa} + \frac{di_b}{dt} L_{ab} + \frac{di_c}{dt} L_{ac} = -(R_a + \omega \frac{\partial L_{aa}}{\partial\theta}) i_a - \frac{\partial L_{ab}}{\partial\theta} \omega i_b - \frac{\partial L_{ac}}{\partial\theta} \omega i_c + v_a + \psi_{r1} n_g \omega \sin(n_g\theta) + 3\psi_{r1} n_g \omega \sin(3n_g\theta)$

$\frac{di_a}{dt} L_{ba} + \frac{di_b}{dt} L_{bb} + \frac{di_c}{dt} L_{bc} = -\frac{\partial L_{ba}}{\partial\theta} \omega i_a - (R_b + \omega \frac{\partial L_{bb}}{\partial\theta}) i_b - \frac{\partial L_{bc}}{\partial\theta} \omega i_c + v_b + \psi_{r1} n_g \omega \sin(n_g\theta - \frac{2\pi}{3}) + 3\psi_{r1} n_g \omega \sin(3n_g\theta - \frac{2\pi}{3})$

$\frac{di_a}{dt} L_{ca} + \frac{di_b}{dt} L_{cb} + \frac{di_c}{dt} L_{cc} = -\frac{\partial L_{ca}}{\partial\theta} \omega i_a - \frac{\partial L_{cb}}{\partial\theta} \omega i_b - (R_c + \omega \frac{\partial L_{cc}}{\partial\theta}) i_c + v_c + \psi_{r1} n_g \omega \sin(n_g\theta + \frac{2\pi}{3}) + 3\psi_{r1} n_g \omega \sin(3n_g\theta + \frac{2\pi}{3})$

The space state form is

$$\begin{bmatrix} L_{aa} & L_{ab} & L_{ac} \\ L_{ba} & L_{bb} & L_{bc} \\ L_{ca} & L_{cb} & L_{cc} \end{bmatrix} \dot{\begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix}} = \begin{bmatrix} -(R_a + \omega\frac{\partial L_{aa}}{\partial\theta}) & -\frac{\partial L_{ab}}{\partial\theta}\omega & -\frac{\partial L_{ac}}{\partial\theta}\omega \\ -\frac{\partial L_{ba}}{\partial\theta}\omega & -(R_b + \omega\frac{\partial L_{bb}}{\partial\theta}) & -\frac{\partial L_{bc}}{\partial\theta}\omega \\ -\frac{\partial L_{ca}}{\partial\theta}\omega & -\frac{\partial L_{cb}}{\partial\theta}\omega & -(R_c + \omega\frac{\partial L_{cc}}{\partial\theta}) \end{bmatrix} \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} +$$

$$\begin{bmatrix} v_a + \psi_{r1} n_g \omega \sin(n_g\theta) + 3\psi_{r1} n_g \omega \sin(3n_g\theta) \\ v_b + \psi_{r1} n_g \omega \sin(n_g\theta - \frac{2\pi}{3}) + 3\psi_{r1} n_g \omega \sin(3n_g\theta - \frac{2\pi}{3}) \\ v_c + \psi_{r1} n_g \omega \sin(n_g\theta + \frac{2\pi}{3}) + 3\psi_{r1} n_g \omega \sin(3n_g\theta + \frac{2\pi}{3}) \end{bmatrix}$$

Where 'dot' denotes time derivative.

CHAPTER 5: PLANT DISCRETIZATION

In early 60´s and 70´s in engineering community Astrm, Goodwin, Middleton and others observed that some discretization methods do not achieve expected improvements if sampling period is approaching to zero. The concept of sampling zeros, finite word length effects, frequency responses sensitivity, round-off noise results were born.

5.1 Step-invariant Discretization

For the basic definition of step-invariant transformation please see [4], p. 33 or [24], p. 33. Basically in this approach the discrete system is designed so its step response is a sampled version of the step response of the analog system. In another words error at sampling instants should be zero.

The step-invariant transformation maps the state matrices in

$\dot{x}(t) = Ax(t) + Bu(t)$

$y(t) = Cx(t) + Du(t)$

as

$(A, B, C, D) \to (A_d, B_d, C, D)$, where

$$A_d = e^{\Delta A}, B_d = \int_0^{\Delta} e^{\tau A} B d\tau$$

Unfortunately this kind of approximation in limit doesn't approximate continuous derivative because when

$\Delta \to 0$ then $A_d \to I, B_d \to 0$

and discrete system obtained by step-invariant transformation is

$x(t_k + \Delta) = A_d x(t_k) + B_d u(t_k)$

$y(t_k) = Cx(t_k) + Du(t_k)$

So when $\Delta \to 0$

$x(t_k + 0) = x(t_k)$

$y(t_k) = Cx(t_k) + Du(t_k)$

5.2 The Delta Operator

Step-invariant transformation has an issue because we would expect that when $\Delta \to 0$ the discrete models approximates the continuous system.

Note that anti-aliasing filter dynamics is not included in above derivation. In order to fix that, see [115], fix is suggested in the form of delta operator δ

$\delta x_k = \frac{x_{k+1} - x_k}{\Delta} = \frac{q-1}{\Delta} x_k$

If we apply that transformation then $(A_d, B_d, C, D) \to (A_D, B_D, C, D)$ where

$A_D = \frac{A_d - I}{\Delta}, B_D = \frac{B_d}{\Delta}$

In this case if $\Delta \to 0$ then $A_D \to A$ and $B_D \to B$.

On Figure 16 given is an example where step responses of continuous versus two different discretization is presented.

5.3 Sampling Speed and Sampling Zeros

Requirement for non-aliasing according to Nyquist criteria determines a lower bound for the sampling rate of a signals, see [3, 28, 115]. On the other hand if we use delta scheme for model discretization the sampling speed could be high as wanted. From practical application view the sampling rate could be as high as it is necessary but not higher. The

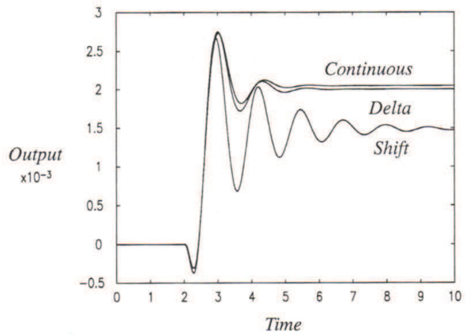


Figure 16: Continuous versus discrete Delta and Shift system response

influence of sampling zeros on quality of the discrete model and implementation cost suggest that upper sampling speed bound should not be crossed. On page 164 of [28] the example is given where discrete-time transfer function has zeros although original continuous system transfer function doesn't have any zero. Discretization process doesn't generate new poles so there is one-to-one relation between continuous transfer and discrete transfer function poles. The example mentioned shows that sampling process may create zeros. The influence of sampling zeros on behaviour of discrete systems shows high dependence of plant model in high frequency area. The high frequency area is usually not modeled well so that is one additional reason why choosing sampling frequency high enough so that influence of sampling zeros is minimized. Nevertheless, [115], page 77, both continuous and discrete models should be considered within a bandwidth of validity, to avoid high frequency modeling errors having a negative impact on design procedures. As a conclusion we may say that if sampling frequency is much higher, say ten times, then design bandwidth influence of sampling zeros is minimal. On the contrary if design bandwidth is comparable with Nyquist frequency ($\frac{\pi}{\Delta}$) then negative influence of sampling zeros is evident. In that case, it seems reasonable to expect that one needs to accurately capture the behaviour of the model in the vicinity of the Nyquist frequency.

5.4 Linear Discrete PM Motor with Stator Winding Fault

Next, we discretize (3.7) for implementation of algorithms in a computer. Suppose that the sampling interval is τ. Let $v_k = v(k\tau)$, $i_k = i(k\tau)$, $g_k = g(k\tau)$. Then, (3.7) is discretized to

$$\begin{aligned} i_{k+1} &= (I - \tau R H^{-1}) i_k + H^{-1} \\ &\cdot \begin{bmatrix} \tau(v_a(k) - e_a(k)) + \kappa\mu(\tau R v_a(k) + L(v_a(k) - v_a(k-1)) \\ \tau(v_b(k) - e_b(k)) + \kappa\mu M(v_a(k) - v_a(k-1)) \\ \tau(v_c(k) - e_c(k)) + \kappa\mu M(v_a(k) - v_a(k-1)) \end{bmatrix}, \end{aligned} \tag{5.1}$$

where we have

$$\begin{bmatrix} e_a(k) \\ e_b(k) \\ e_c(k) \end{bmatrix} = \lambda_M \begin{bmatrix} g_a(k) \\ g_b(k) \\ g_c(k) \end{bmatrix} \equiv \lambda_M g(t).$$

This thesis we investigates motor parameter estimation under normal operating conditions and fault detection. Simulation models will be used to schedule a fault appearance. Starting with a normal operation, a fault is then simulated on Phase a at a certain time. Our enhanced model is then used to represent the voltage-current profiles after the fault. These will be covered in the subsequent sections.

CHAPTER 6: LEAST-SQUARE PLANT IDENTIFICATION

In this thesis the least-squares methods and their improvements will be studied and applied.

6.1 Least-Squares for Permanent Magnet Motor Identification

The least-square identification algorithm is relatively old, discovered by Legandre and Gauss (1795). There are many works, but here we base our expositions on [43] and [91].

Assume that we have n-observation on the plant with p unknown parameters $\theta_1, ...\theta_p$ which should be estimated

$$y_i = \sum_{j=1}^{p} a_{ij}\theta_j + \nu_i$$

where a_{ij} assumed to be known. The measurement noise, ν_i, assumed to be mutually independent random variables with approximately identical distributions. In the matrix notation

$$Y = A\theta + \nu$$

The parameters θ are found by finding minimum of the estimation error

$$\min\left(\sum_i (y_i - \sum a_{ij}\theta_j)^2\right)$$

The solution, assuming that $A^T A$ has full rank the inverse can be found

$$\theta = (A^T A)^{-1} A^T y$$

6.2 Regression Models for Permanent Magnet System Identification

The healthy motor model (3.3) contains four parameters R, L, M, λ_M. For system identification, we rewrite (3.3) in the form of

$$v(t) = Ri(t) + (LI + MH_M)\frac{di(t)}{dt} + \lambda_M g(t) \tag{6.1}$$

where I is the identity matrix and

$$H_M = \begin{bmatrix} 0 & 1 & 1 \\ 1 & 0 & 1 \\ 1 & 1 & 0 \end{bmatrix}.$$

Under the sampling interval τ, (6.1) is discretized to

$$v_k\tau = Ri_k\tau + L(i_k - i_{k-1}) + MH_M(i_k - i_{k-1}) + \lambda_M g_k\tau. \tag{6.2}$$

Denote $\theta = [R, L, M, \lambda_M]'$, $\phi_k' = [i_k\tau, i_k - i_{k-1}, H_M(i_k - i_{k-1}), g_k\tau]$; $y_k = v_k\tau$. It follows that (6.2) can be written in a regression form

$$y_k = \phi_k'\theta. \tag{6.3}$$

It is noted that the dimensions are $y_k \in \mathbb{R}^3$, $\phi_k' \in \mathbb{R}^{3\times 4}$, $\theta \in \mathbb{R}^4$. Also, although physically it is more convenient to view the phase voltages as the input and the currents as the output for the motor models, for system identification we follow (6.3) to view v_k as the output and i_k as the input. As a result, in the sebsequent discussions, output noises will refer to voltage measurement noises and input noises will be current measurement noises.

Due to measurement errors and disturbances, observations are corrupted by noises

$$\widetilde{y}_k = y_k + e_k; \quad \widetilde{i}_k = i_k + \varepsilon_k.$$

Current measurement noises introduce a perturbation on the regressor

$$\widetilde{\phi}'_k = \phi'_k + \delta_k$$

. Consequently, the regression relationship that utilizes measured values is

$$\widetilde{y}_k = (\widetilde{\phi}'_k - \delta_k)\theta + e_k.$$

Here e_k is due to noises on the voltage and δ_k is induced from the current measurement noises.

The joint vector sequence $\{[\varepsilon_k, e_k]\}$ is stationary and strongly ergodic (in the sense of convergence with probability one (w.p.1)) such that $E([\varepsilon_k, e_k]') = 0$, $E(\|[\varepsilon_k, e_k]\|^2) < \infty$, and that both $\{[\varepsilon_k, e_k]\}$ and $\{[\varepsilon_k, e_k]'[\varepsilon_k, e_k]\}$ are ergodic. That is, $\frac{1}{N}\sum_{k=1}^{N}[\varepsilon_k, e_k] \to 0$, w.p.1 as $N \to \infty$, $\frac{1}{N}\sum_{k=1}^{N}[\varepsilon_k, e_k][\varepsilon_k, e_k]' \to S$, where S is a nonnegative definite matrix w.p.1 as $N \to \infty$. Here, $E(\cdot)$ denotes the expectation.

Note that the noises are zero mean, but we do not need the sequences $\{\varepsilon_k\}$ and $\{e_k\}$ to be independent or uncorrelated. A sufficient condition to ensure the ergodicity in the above assumption is that the underlying sequence is a stationary φ-mixing sequence, which is a sequence whose remote past and distant future are asymptotically independent. The well-known results [47, p. 488] then yield that $[\varepsilon_k, e_k]$ and $\{[\varepsilon_k, e_k][\varepsilon_k, e_k]'\}$ are strongly ergodic.

After N observations, denote $Y_N = [\widetilde{y}_1, \widetilde{y}_2, \ldots, \widetilde{y}_N]'$, $Y_N = [y_1, y_2, \ldots, y_N]'$, $\widetilde{\Phi}_N = [\widetilde{\phi}_1, \widetilde{\phi}_2, \ldots, \widetilde{\phi}_N]'$, $\Phi_N = [\phi_1, \phi_2, \ldots, \phi_N]'$, $\Delta_N = [\delta_1, \delta_2, \ldots, \delta_N]'$. Then, $\widetilde{Y}_N = Y_N + E_N; \quad \widetilde{\Phi}_N = \Phi_N + \Delta_N$. From

$\widetilde{y}_k = (\widetilde{\phi}'_k - \delta_k)\theta + e_k$, the observation equation becomes $\widetilde{Y}_N = (\widetilde{\Phi}_N - \Delta_N)\theta + E_N$. When $\widetilde{\Phi}'_N \widetilde{\Phi}_N$ is nonsingular, w.p.1, the standard LS estimate is

$$\theta_N = (\widetilde{\Phi}'_N \widetilde{\Phi}_N)^{-1} \widetilde{\Phi}'_N \widetilde{Y}_N = \left(\frac{1}{N}\widetilde{\Phi}'_N \widetilde{\Phi}_N\right)^{-1} \frac{1}{N}\widetilde{\Phi}'_N \widetilde{Y}_N. \tag{6.4}$$

We illustrate our basic algorithms with the following example. A PM motor has the following true parameters: $R = 2.8750$ (Ω), $L = 0.0064$ (H), $M = -0.0021$ (H), $\lambda_M = 0.1750$ (Wb). This model is simulated in a Matlab platform. The sampling frequency is 100 (KHz) or equivalently the sampling interval is $\tau = 0.01$ (ms). The applied voltage profiles are balanced three-phase sinusoid waveforms of peak value 500 (V) and frequency 60 (Hz). The simulation is run for a total 2000 sampling points. The output (voltage) is corrupted by noise, which is a Gaussian i.i.d. (independent and identically distributed) process of zero mean and standard deviation $\sigma_v = 20$ (V). The LS algorithm (6.4) is applied. Fig. 17 demonstrates the parameter estimation error trajectories. The error is defined as $\|\theta_N - \theta\|$ where $\|\cdot\|$ is the Euclidean norm. In this case, estimation is quite accurate.

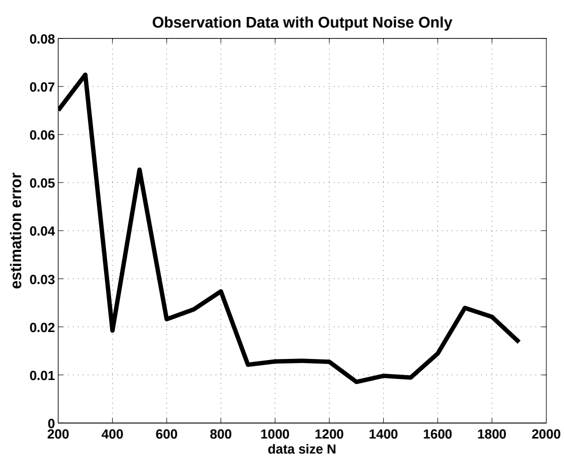


Figure 17: Estimation error trajectories with input noise only

We demonstrate in Section 7 that if the input is also subject to measurement noise, this algorithm will introduce identification bias, namely, parameter estimates will converge to values different from the true value.

CHAPTER 7: ROBUST LEAST-SQUARE IDENTIFICATION

7.1 Robust Least-Square Identification with Bias Correction

Under Assumption 6.2, since Y_N and Φ_N are deterministic, as $N \to \infty$, with probability one,

$$\frac{1}{N}\Phi'_N Y_N \to A;\ \frac{1}{N}\Delta'_N Y_N \to 0;\ \frac{1}{N}\Phi'_N E_N \to 0;$$

$$\frac{1}{N}\Delta'_N E_N \to B; \frac{1}{N}\Phi'_N \Phi_N \to R,\ \frac{1}{N}\Delta'_N \Delta_N \to \Sigma;\ \frac{1}{N}\Phi'_N \Delta_N \to 0,$$

which imply

$$\frac{1}{N}\widetilde{\Phi}'_N \widetilde{Y}_N \to A + B, \quad \frac{1}{N}\widetilde{\Phi}'_N \widetilde{\Phi}_N \to R + \Sigma,$$

for some matrices A, B, R, and Σ. As a result, $\theta_N \to (R+\Sigma)^{-1}(A+B)$ w.p.1. On the other hand, the true parameter satisfies $\theta = R^{-1}A$. Consequently, we have the following theorem.

Theorem 1 *Assume that Assumption 6.2 holds and that R^{-1} exists. Then the least-squares estimate (6.4) is asymptotically biased in that*

$$\lim_{N\to\infty} \big(\theta_N - \theta\big) = (R+\Sigma)^{-1}(B - \Sigma\theta) \quad \textit{w.p.1.}$$

Proof. This follows from

$$\begin{aligned}
\theta_N - \theta &\to (R+\Sigma)^{-1}(A+B) - R^{-1}A \\
&= (R+\Sigma)^{-1}A - R^{-1}A + (R+\Sigma)^{-1}B \\
&= -(R+\Sigma)^{-1}\Sigma R^{-1}A + (R+\Sigma)^{-1}B \\
&= (R+\Sigma)^{-1}(B - \Sigma\theta).
\end{aligned}$$

This completes the proof. □

Identification bias can be corrected if Σ and B are known. The algorithm (6.4) is modified to

$$\theta_N = \left(\frac{1}{N}\widetilde{\Phi}'_N\widetilde{\Phi}_N - \Sigma\right)^{-1}\left(\frac{1}{N}\widetilde{\Phi}'_N\widetilde{Y}_N - B\right). \tag{7.1}$$

It follows from Theorem 1 that this modified θ_N has a desired convergence property. If Σ and B are unknown, we can use statistical methods to estimate them. Then in the bias correction algorithm (7.1), in place of the true Σ and B, we may use their estimates.

Theorem 2 *Under the assumptions of Theorem 1, the estimates in* (7.1) *satisfy*

$$\theta_N \to \theta \quad \textit{w.p.1 as } N \to \infty.$$

Proof. By the strong law of large numbers, as $N \to \infty$,

$$\theta_N \to (R + \Sigma - \Sigma)^{-1}(A + B - B) = R^{-1}A = \theta \quad \text{w.p.1.}$$

$\square$

7.2 Recursive Algorithms for Bias Corrected LS Algorithms

We now introduce a recursive algorithm for (7.1).

Theorem 3 *The estimates θ_N in (7.1) can be updated recursively as*

$$\begin{aligned}
\theta_N &= \theta_{N-1} + K_N\left(\begin{bmatrix} y_N \\ B \end{bmatrix} - \begin{bmatrix} \phi'_N \\ \Sigma \end{bmatrix}\theta_{N-1}\right)\\
K_N &= P_{N-1}[\phi_N, -I]\left(I + \begin{bmatrix} \phi'_N \\ \Sigma \end{bmatrix} P_{N-1}[\phi_N, -I]\right)^{-1}\\
P_N &= P_{N-1} - K_N\begin{bmatrix} \phi'_N \\ \Sigma \end{bmatrix} P_{N-1}
\end{aligned}$$

Proof: From (7.1),

$$\begin{aligned}\theta_N &= \left(\frac{1}{N}\widetilde{\Phi}'_N\widetilde{\Phi}_N - \Sigma\right)^{-1}\left(\frac{1}{N}\widetilde{\Phi}'_N\widetilde{Y}_N - B\right)\\ &= \left(\widetilde{\Phi}'_N\widetilde{\Phi}_N - N\Sigma\right)^{-1}\left(\widetilde{\Phi}'_N\widetilde{Y}_N - NB\right).\end{aligned}$$

Let $P_N = (\widetilde{\Phi}'_N\widetilde{\Phi}_N - N\Sigma)^{-1}$. Since $\widetilde{\Phi}'_N\widetilde{\Phi}_N = \widetilde{\Phi}'_{N-1}\widetilde{\Phi}_{N-1} + \phi_N\phi'_N$, we have

$$\begin{aligned}P_N &= (\widetilde{\Phi}'_N\widetilde{\Phi}_N - N\Sigma)^{-1}\\ &= (\widetilde{\Phi}'_{N-1}\widetilde{\Phi}_{N-1} - (N-1)\Sigma + \phi_N\phi'_N - \Sigma)^{-1}\\ &= (P_{N-1}^{-1} + \phi_N\phi'_N - \Sigma)^{-1}\\ &= \left(P_{N-1}^{-1} + [\phi_N, -I]\begin{bmatrix}\phi'_N\\ \Sigma\end{bmatrix}\right)^{-1}\end{aligned}$$

By the matrix inversion lemma

$$P_N = P_{N-1} - P_{N-1}[\phi_N, -I]\left(I + \begin{bmatrix}\phi'_N\\ \Sigma\end{bmatrix}P_{N-1}[\phi_N, -I]\right)^{-1}\begin{bmatrix}\phi'_N\\ \Sigma\end{bmatrix}P_{N-1} \tag{7.2}$$

Moreover,

$$\begin{aligned}\widetilde{\Phi}'_N\widetilde{Y}_N - NB &= \widetilde{\Phi}'_{N-1}\widetilde{Y}_{N-1} - (N-1)B + \phi_N y_N - B\\ &= \widetilde{\Phi}'_{N-1}\widetilde{Y}_{N-1} - (N-1)B + [\phi_N, -I]\begin{bmatrix}y_N\\ B\end{bmatrix}\end{aligned}$$

Define $K_N = P_N[\phi_N, -I]$. By (7.2),

$$\begin{aligned}K_N &= P_N[\phi_N, -I]\\ &= P_{N-1}[\phi_N, -I](I - \left(I + \begin{bmatrix}\phi'_N\\ \Sigma\end{bmatrix}P_{N-1}[\phi_N, -I]\right)^{-1}\begin{bmatrix}\phi'_N\\ \Sigma\end{bmatrix}P_{N-1}[\phi_N, -I])\\ &= P_{N-1}[\phi_N, -I]\left(I + \begin{bmatrix}\phi'_N\\ \Sigma\end{bmatrix}P_{N-1}[\phi_N, -I]\right)^{-1}\end{aligned}$$

It follows that

$$P_N = P_{N-1} - K_N\begin{bmatrix}\phi'_N\\ \Sigma\end{bmatrix}P_{N-1}$$

Finally,

$$\begin{aligned}
\theta_N &= P_N\left(\widetilde{\Phi}'_N\widetilde{Y}_N - NB\right)\\
&= (P_{N-1} - K_N\begin{bmatrix}\phi'_N\\ \Sigma\end{bmatrix}P_{N-1})(\widetilde{\Phi}'_{N-1}\widetilde{Y}_{N-1} - (N-1)B + [\phi_N, -I]\begin{bmatrix}y_N\\ B\end{bmatrix})\\
&= \theta_{N-1} - K_N\begin{bmatrix}\phi'_N\\ \Sigma\end{bmatrix}\theta_{N-1} + K_N\begin{bmatrix}y_N\\ B\end{bmatrix}\\
&= \theta_{N-1} + K_N\left(\begin{bmatrix}y_N\\ B\end{bmatrix} - \begin{bmatrix}\phi'_N\\ \Sigma\end{bmatrix}\theta_{N-1}\right)
\end{aligned}$$

□

7.3 Errors-in-Variables Identification and Estimation Bias

Under Assumption 6.2, since Y_N and Φ_N are deterministic, as $N \to \infty$, with probability one, $\frac{1}{N}\Phi'_N Y_N \to A$; $\frac{1}{N}\Delta'_N Y_N \to 0$; $\frac{1}{N}\Phi'_N E_N \to 0$; $\frac{1}{N}\Delta'_N E_N \to B$; $\frac{1}{N}\Phi'_N\Phi_N \to C$, $\frac{1}{N}\Delta'_N\Delta_N \to \Sigma$; $\frac{1}{N}\Phi'_N\Delta_N \to 0$, which imply $\frac{1}{N}\widetilde{\Phi}'_N\widetilde{Y}_N \to A + B$ and $\frac{1}{N}\widetilde{\Phi}'_N\widetilde{\Phi}_N \to C + \Sigma$, for some matrices A, B, C, and Σ. As a result, $\theta_N \to (C+\Sigma)^{-1}(A+B)$, w.p.1. On the other hand, the true parameter θ satisfies $\theta = C^{-1}A$. Consequently, we have the following theorem.

Theorem 4 *Assume that Assumption 6.2 holds and that C^{-1} exists. Then the least-squares estimate (6.4) is asymptotically biased in that $\lim_{N\to\infty}\left(\theta_N - \theta\right) = (C+\Sigma)^{-1}(B - \Sigma\theta)$ w.p.1.*

To demonstrate the impact of current measurement noises, we consider the same motor as in Example 6.2. Fig. 18 compares two cases: (1) Only voltage measurements have noises; (2) both voltage and current measurements are subject to noises. The same least-squares algorithm (6.4) is applied to both cases. In the first case, only the output (voltage) is corrupted by noise, which is a sequence of Gaussian i.i.d. random variables with zero mean and standard deviation $\sigma_v = 20$ (V). Since the voltage peak is 500 (V), or equivalently RMS value $500/\sqrt{2} = 353.6$, this amounts to a noise-to-signal ratio of 5.66%. The top plot shows that when no input noise exists, the LS algorithm is quite effective in generating reliable parameter estimates. Then, an input noise is added to the current measurements, which is a Gaussian i.i.d. sequence with zero mean and standard deviation $\sigma_i = 5$ (A). Since the current magnitudes are close to 116 (A) (or 82 RMS), this is about a noise-to-signal ratio of 6.1%. The bottom plot illustrates that the parameter estimation now has a bias, which is about 2.486. Since the size of the parameter vector $\|\theta\|$ is 2.8803, this bias is a relative estimation error 86.3% which is obviously unacceptable. It is noted that this is a persistent bias that does not decrease with an increase in data size. In comparison, without the input noise, the estimation error is below 0.02 or around 0.7%.

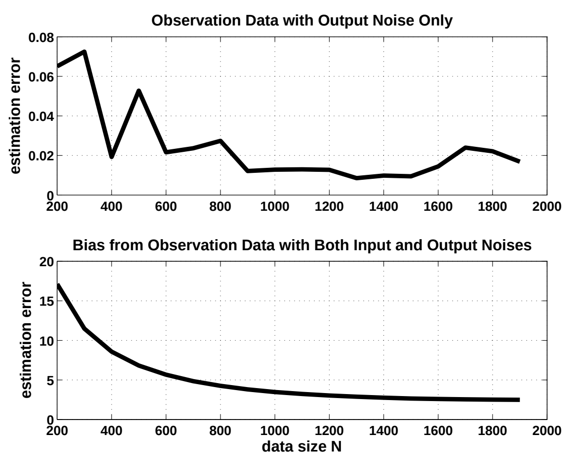


Figure 18: Impact of input and output measurement noise on estimation bias

7.4 Bias Correction by Modified LS Algorithms

Identification bias can be corrected if Σ and B are known. The algorithm (6.4) is now modified to

$$\theta_N = \left(\frac{1}{N}\widetilde{\Phi}'_N\widetilde{\Phi}_N - \Sigma\right)^{-1}\left(\frac{1}{N}\widetilde{\Phi}'_N\widetilde{Y}_N - B\right). \tag{7.3}$$

If Σ and B are unknown, we can use statistical methods to estimate them. Then in the bias correction algorithm (7.3), in place of the true Σ and B, we can use their estimates.

Theorem 5 *Under the assumptions of Theorem 1, the estimates in* (7.3) *satisfy* $\theta_N \to \theta$, *w.p.1 as* $N \to \infty$.

The modified LS algorithm (7.3) can be recursified for real-time computational efficiency. The following recursive algorithm was introduced in [94].

Theorem 6 *[94] The estimates* θ_N *in (7.3) can be updated recursively as*

$$\begin{aligned}
\theta_N &= \theta_{N-1} + K_N\left(\begin{bmatrix}\widetilde{y}_N\\ B\end{bmatrix} - \begin{bmatrix}\widetilde{\phi}'_N\\ \Sigma\end{bmatrix}\theta_{N-1}\right)\\
K_N &= P_{N-1}[\widetilde{\phi}_N, -I]\left(I + \begin{bmatrix}\widetilde{\phi}'_N\\ \Sigma\end{bmatrix}P_{N-1}[\widetilde{\phi}_N, -I]\right)^{-1}\\
P_N &= P_{N-1} - K_N\begin{bmatrix}\widetilde{\phi}'_N\\ \Sigma\end{bmatrix}P_{N-1}
\end{aligned}$$

Example 7 Continuing the study from Example 7.3, we note that when the input noise exists and bias correction method is not applied, at the exit point ($N = 2000$) the norm of the estimation error is 2.486 (a sample result in simulation). Now we apply our bias correction algorithm, the estimation error at the exit point is reduced to 0.0061.

7.5 Identification Robustness through Knowledge Inclusion

In early 60´s only 'ideal' measurement noise was considered. At that time Gaussian noise was assumed to be very good approximation for developing filtering and identification design theory. Later was noticed that algorithms developed under this assumption luck robustness because sometimes the noise in practice was not even close to normal. In such cases the 'optimal systems' demonstrated far from optimal behaviour. Later people understood that there are other types of the luck of information which could not be modeled by normal noise. An example of such random dynamics would be parameter variation over time. These errors are not randomly oscillating around a real value but they are sort of bias. In the case of plant identification very often we a priori know possible value range of identified variables. For example, in the case of electrical motor, we know that resistance, self-inductance cant be negative. If we know that motor doesn't have fault then we can even be sure that parameter belongs to certain interval. It is logical to assume that knowledge can be used to improve convergence of identification algorithm. Classical Least-square method does not use a priory available knowledge. There are two approaches if using a priory available knowledge. In the case estimated parameter value is out of range (set membership) the sample can be considered as outliers and it can be thrown out. In the second approach least square method is extended by solving minimum square problem with constraints. Later, in this dissertation, some discussion regarding how to make likelihood ratio more robust, will be added in the section 8.5.

7.6 Estimation Subject to Linear Constrains

Effort to get benefits of a priori knowledge to improve identification convergence speed or algorithm resolution started in statistics with papers dealing with batch (matrix) processing of data. See for example [86], [60], [103]. The recursive least-square with a priori knowledge in the form of linear equalities or inequalities were considered [119]. Let assume that θ is unknown parameter and that constraint or knowledge about θ is given by

$A\theta = B$

Some authors call it linearly constrained estimation problem or least square equality (LSE) problem. The least square inequality (LSI) has additional equation as

$A\theta \geq B$

The solution to unconstrained problem can be found from

$X_n^T X_n \theta = X_n^T Y_n$

if, $X_n^T X_n$ doesn't have inverse we can solve problem by finding generalized inverse (not unique). For example using Moore-Penrose inverse

$\theta = (X_n^T X_n)^+ X_n^T Y_n$

The recursive solution, presented in [119] is on the other hand

$\theta_{n+1} = \theta_n + K_{n+1}(y_{n+1} - \theta_n^* x_{n+1})^*$, where '$*$' stands for complex conjugation,

$K_{n+1} = P_n x_{n+1}/(1 + x_{n+1}^* P_n x_{n+1})$,

$P_{n+1} = (X_{n+1} X^*{}_{n+1})^{-1} = (P_n^{-1} + x_{n+1} x_{n+1}^*)^{-1} = (I - K_{n+1} x_{n+1}^*) P_n$

By using an orthogonal basis of the null space of A, the linear constraint problem has solution if and only if $\begin{bmatrix} A \\ X_n^* \end{bmatrix}$ has full rank. In that case we have recursive solution as

$\theta_n = A^+B + (X_n^* P)^+ (Y_n^* - X_n^* A^+ B)$

It can be shown that LSE and RLS problems have the same type of recursive solution except for initial values. For RLS the initial values are

$$\theta_{n_0} = (X_{n_0} X_{n_0}^*)^{-1} X_{n_0} Y_{n_0}^*$$

and

$$P_{n_0} = (X_{n_0} X_{n_0}^*)^{-1}$$

For RLE the initial values are

$\theta_{n_0} = A^+B + (P X_{n_0} X_{n_0}^* P)^+ X_{n_0} (Y_{n_0}^* - X_{n_0}^* A^+ B)$

$$P_{n_0} = (P X_{n_0} X_{n_0}^* P)^+$$

The solution to LSI is essentially combination of RLS and LSE solutions.

7.7 Outliers, Deleting or Ignoring Measurements

Time series observations, see [10], [43], are sometimes affected by non-characteristics events, disturbances or errors that create spurious effects in the data series which would disturb identification convergence by having substantial effects on the behaviour os sample autocorrelation. Such unusual, 'non-helpful', observations maybe referred as *outliers*. Depending on type of data processing the observation data it is necessary either to delete outliers, in batch processing, or to ignore outliers in the case or real-time recursive data processing. However, since in practice the presence of outliers is often not known at the start of analysis additional procedures for detection of outliers and assessment of their possible impacts are important.

7.8 Outliers in the Case of Electrical Motors Data Collections

We identify parameters and fault of electrical motors by minimizing error between analog hardware model and discretized model where parameters values are computed through ongoing identification process using input and output measured signal values. Electrical motors, like permanent magnet motors, are supplied from a voltage inverter where signal is jumping from one level to the other (PWM modulation). Let us consider the moment when input signal to electrical motor changes the level from zero to the other levels. The time domain edge effect is caused by sampling below Nyquist for fast PWM signal level changes and finite computation throughput. Here we consider effect of frequency overlapping due to high band dynamics of input signal or dually and not sufficient matching sampling speed.

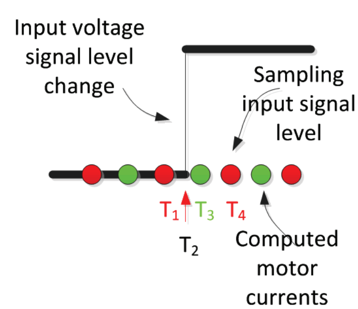


Figure 19: Finite sampling and computation speed effect

In figure 19 red dots represent sampling points. Based on sampled values and based on discrete plant model the estimation algorithm is going to compute estimate of the plant output signal. If time-constant of the plant is smaller then computation time the estimation algorithm will have some delay relative to plant output. Figure 19 represent the case when input signal rises in between two sample points so that estimation algorithm is informed about input rise to the new level with a delay which can be close to the length of sampling interval. This delay is causing an spike in the error signal. On 20 that effect is represented with black pulse (real physical signal) versus estimated plant output in red. In blue we have resulting error signal.

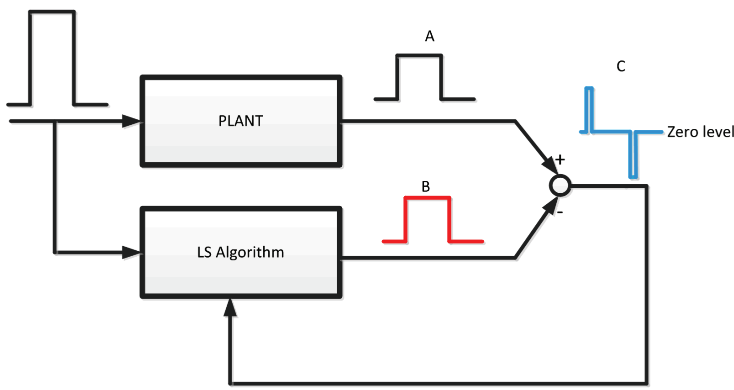


Figure 20: Noise generation due to sampling speed below Nyquist

In practice the input signal is sometimes in hundred volts so above effect can produce spikes of 10^2 when, on the other hand we try to identify size of elements like R, L, M or κ which are in the range of 10^{-3}. It is obvious that identification of electrical motors controlled by inverters requires highly robust identification schemes.

7.9 Case Studies of Parameter Estimation

Practical motors involve certain physical system structures, nonlinearities, auxiliary driving circuits, and time delays. This section includes some more realistic simulation studies that accommodate further motor details.

Two types of stator construction are common for PM machines: sinusoidal winding distribution for permanent magnet synchronous machines (PMSM) and concentrated winding for brushless DC (BLDC) motors. In the first case, the back emf is sinusoidal. The back emf under concentrated winding is trapezoidal. One important difference between these two types is that synchronous machines have continuous currents through all windings (180-degree current leads). In contrast, BLDC machines will have "square" currents with 120-degree leads. Consequently, for each winding there is a time interval when there is no current through a particular winding.

Typical PM configurations include the six-step controlled PM motor shown in Fig. 11, the filed-oriented control (FOC), and the self-controlled system. In the six-step motor, its inverter has six signal levels and requires the lowest closed-loop bandwidth. Sensor delay is a critical parameter because it results in model mismatch. The FOC motor directly controls the stator rotating magnetic field on the rotating frame to provide maximal torque generation and to ensure smoothness of rotor movements. The self-controlled operation is a simplified FOC that employs a stator-based coordinate frame. It is simple in construction, but requires high bandwidths, generates more noise, and is less smooth in rotor movements than the other two types [78].

We now present simulation studies for stator winding parameter identification under normal operating conditions. The motor is a six-step controlled motor with sinusoid state winding. The motor true parameters are the same as in Example 6.2. In this case, R, L, M, and λ_M are to be estimated under a closed-loop configuration. The model sampling time is 0.1 ms. A total of 10000 data points are used in this study. Due to PWM control circuits, the driving voltages' profiles are no longer sinusoid waveforms. The phase current waveforms are also quite different. These are shown in Fig. 21.

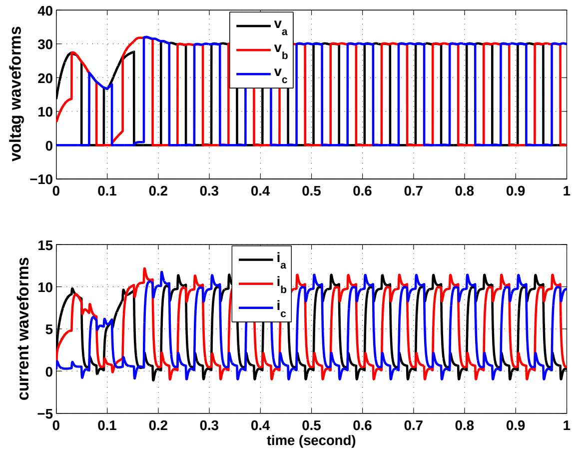


Figure 21: Phase voltage and current profiles

To understand further the impact of current measurement noises, we compare two cases: (1) Only voltage (output in system identification) measurements have noises; (2) both voltage and current measurements are subject to noises. The least-squares algorithm (6.4) is applied. In the first case, only the output (voltage) is corrupted by noise, which is a sequence of Gaussian i.i.d. random variables with zero mean and standard deviation $\sigma_v = 50$ (V). Estimates are shown in Fig. 22. The top plot shows that when no input noise exists, the LS algorithm generates highly accurate estimates. When an input noise is added to the current measurements, which is a Gaussian i.i.d. sequence with zero mean and standard deviation $\sigma_i = 10$ (A), the bottom plot illustrates that the parameter estimation has a bias, which is about 2.1, or a relative estimation error 72%. This is a persistent bias that does not decrease with an increase in data size.

The bias correction algorithm (7.3) is then applied. The estimated parameter values at the exit point are listed in Table 1. The norm of the estimation error is 0.011, or a relative

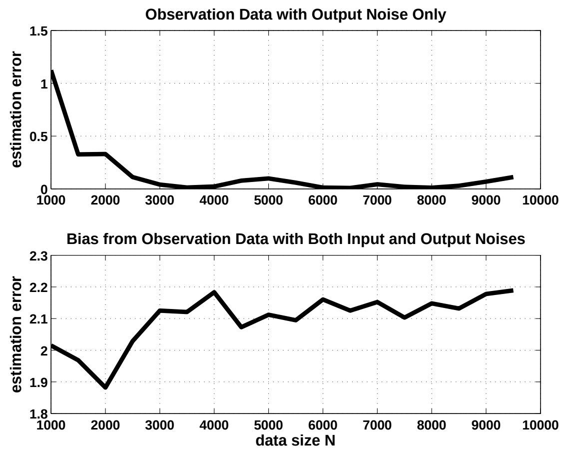


Figure 22: Impact of input and output measurement noise on estimation bias

error 0.3826%.

Table 1: Estimates from Bias-Corrected LS Algorithm

	R	L	M	λ_M
True Values	2.875	0.0064	-0.0021	0.1750
Estimates	2.8720	0.0063	-0.0022	0.1644
Estimation Errors	0.003	0.0001	-0.0001	0.0106

Here we present simulation results for motor parameter identification where sampling speed is 'natural', i.e. motor with six-step control loop have usually one order sampling speed in implementation.

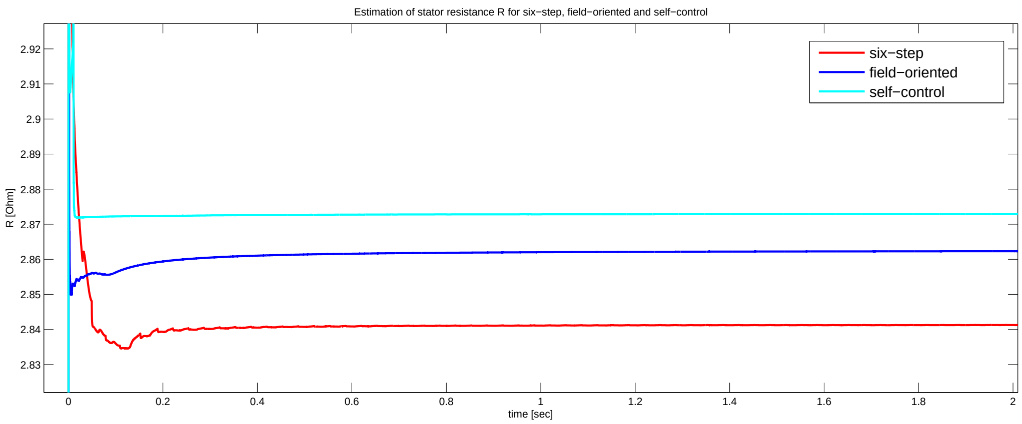


Figure 23: Stator $R = 2.875\Omega$ resistance estimation

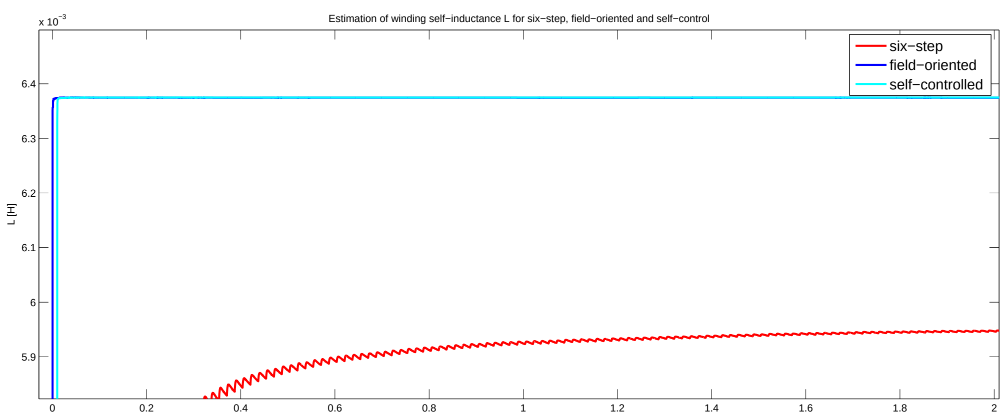


Figure 24: Stator $L = 0.0064H$ inductance estimation

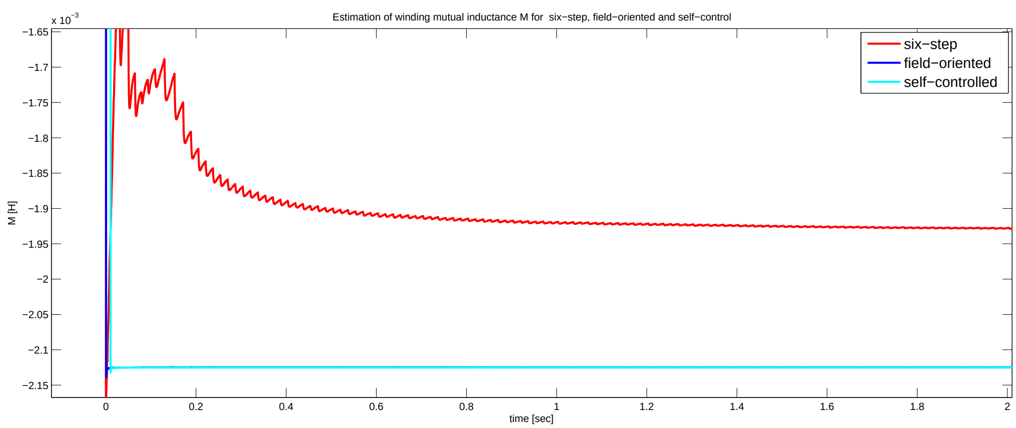


Figure 25: Stator $M = -0.0021H$ mutual inductance estimation

7.10 Fast Tracking and Forgetting Factors

Faults are sudden changes in motor model structures and parameters. When a fault occurs, the identification algorithms must detect such changes accurately and quickly. If large historical data are used in system identification, the new data that reflect the fault will have small impact on the overall parameter estimation, leading to a very slow detection process. The standard LS algorithm minimizes $\min_\theta \sum_{k=0}^{N}(y_k - \phi_k'\theta)^2$ in which all data are equally weighted.

One useful technique to overcome this drawback is to discard old data in a systematic way so that the new data will have more weight in the identification process. This can be achieved by adding a forgetting factor λ in the least squares criterion: for $0 < \lambda < 1$, we modify the optimization problem to $\min_\theta \ \sum_{k=0}^{N} \lambda^{N-k}(y_k - \phi_k'\theta)^2$, which exponentially weights down old data. In its matrix form, this is equivalent to

$$\min_{\theta} \ (Y_N - \Phi_N\theta)' W_N (Y_N - \Phi_N\theta) \tag{7.4}$$

where $W_N = \mathrm{diag}[\lambda^N, \lambda^{N-1}, \ldots, \lambda, 1]$. When $\lambda = 1$, it is reduced to the un-weighted LS algorithm. When λ is close to 0, only most recent data are used in estimating parameters. λ is called a "forgetting factor." There is a key trade-off in selecting λ. If λ is close to 1, then historical data remain heavily weighted. Consequently, fault detection will be slow. On the other hand, if λ is small, the fault detection will be faster, but noise attenuation capability will be compromised, which follows from the laws of large numbers [47].

Let $Q_N = W_N^{1/2}$. Then, (7.4) can be written as $\min_\theta \ (Y_N - \Phi_N\theta)' W_N (Y_N - \Phi_N\theta) = \min_\theta \ (Q_N Y_N - Q_N\Phi_N\theta)'(Q_N Y_N - Q_N\Phi_N\theta)$ whose solution can be obtained by the LS result with Y_N replaced by $Q_N Y_N$ and Φ_N by $Q_N \Phi_N$, as

$$\theta_N = (\Phi_N' W_N \Phi_N)^{-1} \Phi_N' W_N Y_N. \tag{7.5}$$

When both input and output noises are taken into consideration, (7.5) becomes

$$\theta_N = (\widetilde{\Phi}_N' W_N \widetilde{\Phi}_N)^{-1} \widetilde{\Phi}_N' W_N \widetilde{Y}_N. \tag{7.6}$$

However, when input noises cause bias in LS estimates, (7.6) will be subject to bias as well. We note that $Y_N = \Phi_N \theta$, which implies $Q_N Y_N = Q_N \Phi_N \theta$. As a result, $\theta = (\Phi_N' W_N \Phi_N)^{-1} \Phi_N' W_N Y_N$. On the other hand,

$$\begin{aligned} \theta_N = &((\Phi_N + \Delta_N)' W_N (\Phi_N + \Delta_N))^{-1} \\ &\times (\Phi_N + \Delta_N)' W_N (Y_N + E_N). \end{aligned}$$

Under Assumption 6.2, $E(\Phi_N' W_N E_N) = 0$, $E(\Delta_N' W_N Y_N) = 0$, $E(\Delta_N' W_N \Phi_N) = 0$. Denote $E(\Delta_N' W_N \Delta_N) = \Sigma_N$, $E(\Delta_N' W_N E_N) = B_N$. Then, the modified LS estimation (for bias correction) with forgetting factor is given by

$$\theta_N = (\widetilde{\Phi}_N' W_N \widetilde{\Phi}_N - \Sigma_N)^{-1} (\widetilde{\Phi}_N' W_N \widetilde{Y}_N - B_N). \tag{7.7}$$

We should point out that since $0 < \lambda < 1$, the factor $1/N$ in (7.3) is no longer needed here. We now derive a recursive algorithm for (7.7). Let $\Sigma = E(\delta_N' \delta_N)$ and $B = E(\delta_N' e_N)$. By stationarity, these quantities do not depend on N.

Theorem 8 *Given a forgetting factor $0 < \lambda \leq 1$, the bias-corrected LS estimate θ_N with* *forgetting factor λ in (7.7) can be updated recursively as*

$$
\begin{aligned}
\theta_N &= \theta_{N-1} + K_N \left(\begin{bmatrix} \widetilde{y}_N \\ \\ B \end{bmatrix} - \begin{bmatrix} \widetilde{\phi}'_N \\ \\ \Sigma \end{bmatrix} \theta_{N-1} \right) \\
K_N &= P_{N-1}[\widetilde{\phi}_N, -I] \left(\lambda I + \begin{bmatrix} \widetilde{\phi}'_N \\ \\ \Sigma \end{bmatrix} P_{N-1}[\widetilde{\phi}_N, -I] \right)^{-1} \\
P_N &= \frac{P_{N-1}}{\lambda} - K_N \begin{bmatrix} \widetilde{\phi}'_N \\ \\ \Sigma \end{bmatrix} \frac{P_{N-1}}{\lambda}.
\end{aligned}
$$

Some values of forgetting factors influence stability of the identification scheme.

CHAPTER 8: ABRUPT CHANGE DETECTION

Signal detection scheme, in this dissertation, is used in two situations:

1. Winding fault detection is performed by detecting when parameter $\kappa > 0$
2. The outliers detection consists in determination when sampled values are outside predetermined range.

In many industrial applications, see [5],[35], there is a need for optimal, i.e. robust and fastest possible, detection of abrupt changes. In this thesis the abrupt changes in phase currents are caused by winding faults. The key difficulty in change detection is intrinsic character of changes resulting in very often impossibility of direct observation and, also very often, because these changes are masked with measurement noise and other spurious effects. Usually, [5], abrupt changes are defined as any change in the parameters of the system that occurs either instantaneously or at least very fast with respect to the sampling period of measurements. Abrupt changes are in the sense that these signal changes mark fundamental change in model behaviour when, even amplitude wise, the change could be very small. Despite difficulties the goal is always to detect plant change behaviour as fast as possible. It is worth observing that detection of abrupt changes are very dependent on the process of data collection and identification. For example one of mechanisms to optimize abrupt model change detection is to have optimally selected "forgetting factor", to perform sampling of optimal speed and the keep whole system stable.

Depending on applications there are many different algorithms for abrupt change detection. For some other practical alternative methods for change detection, beyond mentioned

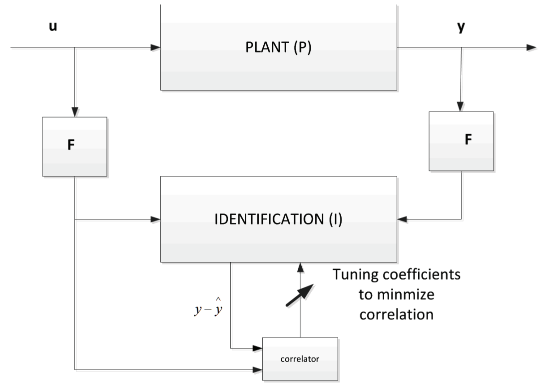


Figure 26: Limiting observed plant dynamics to identification model

above, please see [35]. //Forgetting factor is used in identification if system parameters changes value during time. Determining right forgetting factor is very important because it influences the identification algorithm convergence and it can lead to instability, [12]. Fault detection algorithm is one example where we need forgetting factor less than one in order to be able to detect winding fault in fastest possible way. The forgetting factor could be raised to a value of near 1 when there exists some certitude that the process being identified is not changing. The identification convergence properties have been studied by Astrom, [2], for stationary process, by Ljung, [70]as generalization of previous results. For the other contributions to the field in early seventies and eighties please see [12].

Previously it was showed, in time domain, that high impulse noise can be generated if sampling for identification is done directly on input and output signals, see Figure 20. In order to avoid impulse noise generation due to high dynamics of input signals, see Figure 26, sampling is done only after both input and output signals are filtered using the same hardware filters. This method is limited to linear identification although.

8.1 Binary Decisions

In many practical situation, like for fault detection, the decision algorithm has to decide between two hypothesis H_0 : "no fault present" and H_1 : "fault present". In general we can define hypothesis as statements of possible decisions that are being considered. In binary case, only two outcomes are possible, hypothesis H_0 is commonly called the *null hypothesis*, H_1 *the alternative hypothesis*. Let

$$C(H_1|s)$$

denotes the cost of accepting hypothesis H_1 if signal s is received. The strategy in a binary decision is that we pick H_1 hypothesis which cost less, i.e.

$$C(H_1|s) \leq C(H_0|s)$$

If the costs are the same for both hypothesis then we accept H_1 if hypothesis is of higher probability i.e. that, [112],

$$\Pr(H_1|s) \geq \Pr(H_0|s)$$

or

$$\frac{\Pr(H_1|s)}{\Pr(H_0|s)} \geq 1$$

.

In practice we usually operate with probability density functions. The decision rule, that H_1 if hypothesis is accepted in terms or probability density functions would be

$$\Pr(H_1|s \leq S \leq s+ds) \geq \Pr(H_0|s \leq S \leq s+ds)$$

Using Bayes probability rule the probability of

$$\Pr(H_1|s \leq s \leq v)$$

can be expressed as

$$\Pr(H_1|s \leq s \leq s+ds) = \frac{\Pr(s \leq s \leq s+ds|H_1)P(H_1)}{\Pr(s \leq s \leq s+ds)}$$

where

$$\Pr(H_1)$$

is the probability that H_1 is true. Note that

$$\Pr(s \leq s \leq s+ds)$$

is probability that measured signal s stays in the interval

$$s \leq s \leq s+ds$$

during measured set of data based on which we are trying to make decision. Let signal S as random variable has density function $p(s)$. Thus

$$\Pr(s \leq S \leq s+ds) = p(s)ds$$

. Similarly

$$\Pr(H_1|s \leq S \leq s+ds) = p_1(s)ds$$

and

$$\Pr(H_1|s \leq S \leq s+ds) = \frac{p_1(s)ds\,\Pr(H_1)}{p(s)ds}$$

In the limit for arbitrarily small ds,

$$\Pr(H_1|s \leq S \leq s+ds) = \frac{p_1(s)\,\Pr(H_1)}{p(s)}$$

On the other hand we have

$$\Pr(H_0) = 1 - \Pr(H_1)$$

, and similarly

$$\Pr(H_0|s \leq S \leq s+ds) = \frac{p_0(s)[1-\Pr(H_1)]}{p(s)}$$

Therefore, finally decision rule to choose H_1 is

$$\frac{p_1(s)}{p_0(s)} \geq \frac{\Pr(H_1)]}{1-\Pr(H_1)}$$

In the case when a priori probabilities are known, the criterion of minimum error probability is generally used. In some other cases, however, the a priori probabilities are difficult to determine. For such systems Neyman-Pearson is used. In the case of fault detection the objective is to maximize the probability of detection for a given probability of false alarm. This objective can be accomplished by using a likelihood ratio test. The celebrated Neyman-Pearson lemma tells us how to find the most powerful test of the size α for testing simple hypothesis H_0 versus simple hypothesis H_1.

8.2 Best Tests of Simple H_0 versus Simple H_1

We call simple hypothesis H any assumption concerning hypothesis in question that can be reduced to a single value. In practice hypothesis will be stated against parameters of probability distribution, see [5], page 127.

The power of a statistical test is the probability that it correctly rejects the null hypothesis when the null hypothesis is false (i.e. the probability of not committing a Type II error). That is,

$$power = P_r(reject\, null\, hypothesis | null\, hypothesis\, is\, false)$$

It can be equivalently thought of as the probability of correctly accepting the alternative hypothesis when the alternative hypothesis is true. Power analysis can be used to calculate the minimum sample size required so that one can be reasonably likely to detect an effect of a given size.

Basis of Neyman-Pearson approach, see [66], [39], is that for decision of accepting or rejecting hypothesis in binary case is necessary to consider cost of accepting H_1 and rejection H_0 hypothesis. Detecting winding fault when there is no fault would lead to disconnection of "faulty" phase and unnecessary reducing vehicle power. Sudden reduction of vehicle power in critical situation may lead to traffic accidents so the cost of this kind of faulty decision must be very high. Suppose that tests consists in accepting the hypothesis whenever a test T is greater than or equal to a critical value c.

$$\alpha = \Pr(T \geq c)$$

A necessary condition for optimal decision design is to determine c so that α, cost of false rejection, is minimal or acceptably small. This condition is not sufficient because we can make $\alpha = 0$ by never accepting hypothesis that fault exists. Of course, in that case we do not have fault detection mechanism. So the optimal decision mechanism must be based on minimizing the other possible wrong decision, rejecting hypothesis that fault exist when

$$\beta = \Pr(T \leq c)$$

These two requirements are contradictory and mechanism for this optimization is to determine length of test, i.e. how many sampling points we need to have before we make acceptable decision. In the case when we have full statistical knowledge an optimization scheme, e.g. Lagrange multipliers, can be used to find an optimal solution for c. As an example we can take the case when statistics of two hypothesis is Gaussian. In that case, assuming simple hypothesis, 27, c is computed as

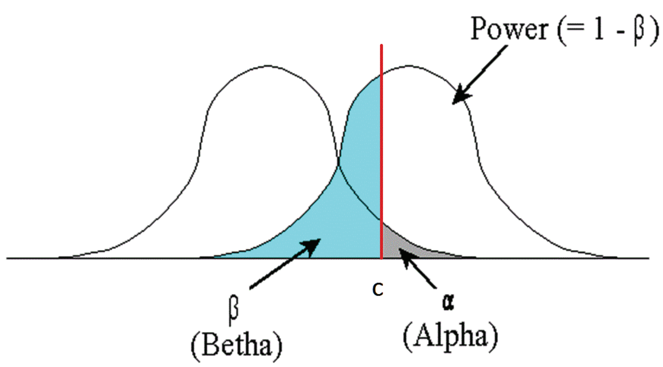


Figure 27: Decision threshold defined by Neyman-Pearson

level of decision threshold such that decision costs satisfy design requirements. In this case we would like to push threshold c enough high so that both

$$\alpha = \Pr(T \geq c)$$

and

$$\beta = \Pr(T \leq c)$$

are sufficiently small. In general case the solution to requirements may not exist. The example would be when mean values of distribution for and for H_0 are H_1 very close to each other.

Although above approach to decision problem is absolutely reasonable it is not robust because it hinges on the assumption that probability distributions for H_0 and H_1 are known and that estimation of measurements is not biased. In industrial practice any of these assumptions may not be satisfied: the noise may have unknown and not stationary characteristics, noise can be correlated and the distribution of hypothesis H_0 and H_1 may not be the same and it could be time dependent. Neyman-Pearson criteria is part of so called 'parametric statistics'. In this case to determine optimal decision we relay on the a priori knowledge of the decision problem: we assume certain type of statics to characterize hypothesis H_0 and H_1 and that statistics can be characterize with set of parameters.

At the end let add that there are other schemes for hypothesis testing beside Neyman-Pearson: Bayesian, Minimax, to mentioned only few

8.3 Best Tests of Simple H_0 versus Composite H_1

In practice we are most often interested in test of composite rather than simple hypothesis. A simple hypothesis is when we trying to make decision regarding single parameter which may take a single value but in the case of a composite hypothesis we are dealing with range of values. An example for composite hypothesis is when we are trying to detect if mean of distribution may belong to certain interval (uncountably many possible values in this case). Unfortunately, in the case when we are working with composite hypothesis, uniformly-most powerful test very often may not exist,[92]. Our goal here is to use detection theory to detect winding fault. In the case of no fault the parameter κ is a zero and being positive if fault exists. The complex hypothesis, in this case, should be formulated as $\{\kappa : \kappa > 0\}$. For this way formulated composite hypothesis the most uniformly most powerful test exists, [92], page 103.

8.4 Detecting a DC signal in Additive White Gaussian Noise

Parameter $\kappa > 0$ can happen for many different cases of winding shorts, different insulation resistance, etc. The alternative hypothesis according to Zacks, [116], could be described by a family of distributions. If that family has only one unknown parameter then hypothesis is simple, otherwise is a composite. In our case, as explained above, H_1: $\kappa > 0$ is a composite hypothesis. Now, [106], we are going to consider the binary hypothesis

$$H_0 : \ X_1, ..., X_n \overset{iid}{\sim} N(0, \sigma^2)$$

$$H_1 : \ X_1, ..., X_n \overset{iid}{\sim} N(\mu, \sigma^2), \ \mu > 0$$

and assume that $\sigma^2 > 0$ is known. The first hypothesis is simple, but H_1 is composite because only what we know is that $\mu > 0$. Please also note that here we consider that decision will be based on n samples. Later we will try to optimize necessary n to make decision based on Shiryaev's stopping rule. In practice the decision process is usually based on many samples to improve the quality of the test, that it is, to reduce probability of error. In this case the likelihood ratio test takes the form

$$\frac{\prod_{i=1}^{n} \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{1}{2\sigma^2}(x_i-\mu)^2}}{\prod_{i=1}^{n} \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{1}{2\sigma^2}{x_i}^2}} = \frac{\frac{1}{(2\pi\sigma^2)^{n/2}} e^{\frac{1}{2\sigma^2}\sum_{i=1}^{n}(x_i-\mu)^2}}{\frac{1}{(2\pi\sigma^2)^{n/2}} e^{\frac{1}{2\sigma^2}\sum_{i=1}^{n}{x_i}^2}} \underset{H_0}{\overset{H_1}{\gtrless}} \gamma$$

We can simplify expression with applying logarithm to both sides of inequality (monotonic function preserves inequality), which gives us log-likelihood test

$$\frac{-1}{2\sigma^2}(-2\mu \sum_{i=1}^{n} x_i + n\mu^2) \underset{H_0}{\overset{H_1}{\gtrless}} \log(\gamma)$$

assuming $\mu > 0$, this is equivalent to

$$\sum_{i=1}^{n} x_i \underset{H_0}{\overset{H_1}{\gtrless}} \nu$$

with

$$\nu = \frac{\sigma^2}{\mu} \ln \gamma + \frac{n\mu}{2}$$

where we can choose ν to optimize trade-off between two types of error.

8.5 Robust Signal Detection

Conventional design procedures for optimum signal detection often require an exact knowledge of the statistical behaviour both of the signal of interest and of the noise corrupting measurements. Actually we can prove decision process optimality by starting from mathematically described context of signal detection where both signal and noise must be expressed using statistical models. Statistical models are fully specified when type of probability densities, correlation and its parameters are known. Based on specified stochastic parameters, type of distribution, the application of chosen optimization scheme will produce, assuming also that there is a solution, an optimal detection procedure. For example if, based on Neyman-Pearson approach we use assumption that noise of H_0 and H_1 are statistically the same where in practice one of distributions has higher divergence then the designed threshold based on faulty information will not be optimal. In order to design for robustness we must first specify a measure of robustness of the scheme with respect to a class of allowable conditions at the signal and noise level. One such scheme used is the worst case performance of a scheme over a class of signal/noise conditions. If the worst scheme performance is acceptable we may say that scheme is robust.

Beside parametric statistics exist also 'nonparametric statistics' which is more robust but less optimal in general. Roughly speaking, a nonparametric procedure is a statistical procedure that has certain desirable properties,[40], which holds under relatively mild assumptions regarding underlying experiment. For some authors the terms nonparametric and distribution-free are often used interchangeably although they are not synonyms. Nonparametric procedures are applicable in many situations where normal theory procedures cannot be utilized. Many nonparametric procedures require just the ranks of the observations, rather than the actual magnitude of the observations, whereas the parametric procedures require the magnitudes.

8.6 Nonparametric Winding Fault detection

In this dissertation the presence and ratio of winding fault is modeled through parameter κ. If fault exists then κ is positive, otherwise κ is zero. Therefore the existence of stator fault detection could be performed using the same approach as in communication for signal presence existence. From statistical point of view the detection of κ being zero or positive can be considered as detecting if probability distribution has mean zero or not (assuming that noise has zero-mean).

In practice if signal-noise ratio is high then simple deterministic threshold crossing scheme could be used to detect fault. To be able to argue optimality in speed detection the more formal approach must be undertaken. So far we assumed that distributions are normal. Justification for that was that decision on hypothesis was taken on signal produced by least-square regression so we assume that only , what remains in that signal, is pure randomness. But robustness of decision process can be further improved if right test is designed. Based on inherently present symmetry of polyphase motors the homogeneity test of [87] is proposed. The hypothesis for modified homogeneity or that fault doesn't exist is probability that distributions of all phase currents are the same

$$H_0 : d_a = d_b = d_c$$

In the case of [87] the mean is used but here we replace 'mean' with 'distribution' where 'distribution' can be limited by certain number of moments. This way we are not limited to any particular distribution and still have all information necessary not only for fault detection but also for isolation.

8.7 Measuring Robustness of an Algorithm

While classical statistics assumes that statistical model is known and then trying to determine plant probable behaviour at specified moment, the goal of robust methods is to develop estimates which have "good" behaviour in the "vicinity" of the assumed plant model. In another words the sensitivity of estimates should not change much if plant model stays in a priori defined neighborhood of the model. In classical regression setup it is assumed that errors of measurements occur only in the response variable (Y), while explanatory variables (A) are measured without error.

$$Y = A\theta$$

This is rarely true. In order to be able to measure robustness of an identification algorithm we must be able to compute sensitivity of the identification method as a function of model change. In another words we should be able to calculate impact of measurement errors on estimated regression coefficients, see [16].

CHAPTER 9: FAULT TOLERANT MOTOR CONTROL

For winding fault detection it will be assumed that at most one fault may exist at the time. Indirectly we assume that after fault has been detected the motor will be serviced.

9.1 Inter-Turn Fault

Fig. 28 shows rotor speed trajectories for a six-step controlled motor when an inter-turn fault happens in Phase a at $t = 2$ second with fault bypass resistance $R_f = 100$ (Ω). It is noted that when a fault happens the closed-loop regulation has difficulty in maintaining the required rotor speed if the leakage insulation is close to a short circuit. On the other hand, we will demonstrate later that if R_f is above 10 K Ω, RPM fluctuations can not be used for fault detection, see Fig. 31. We will present a new detection algorithm which can detect such a fault with accuracy.

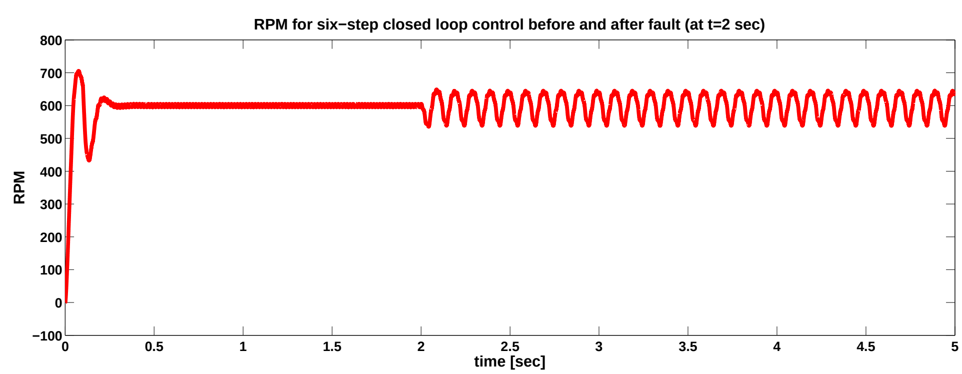


Figure 28: Six-step PID control, winding fault at $t = 2s$, $R_f = 100$ Ω

9.2 Estimation of κ

The estimation algorithms under normal operating conditions provide nominal values of balanced stator winding parameters. In this section, we concentrate on fault detection. Fault detection methods for multi-phase electrical motors can take advantage of balanced phase designs. Since all phases are symmetric, faults will alter parameter values and create an imbalanced condition between any pair of phases that can be used for detecting and isolating faults. Stator winding faults can spread quickly. Without prompt detection and protective actions, the condition can deteriorate rapidly. As a result, it is extremely important that fault detection is fast, which creates a challenging situation for designing identification algorithms. Rotor speed fluctuations can be affected by both faults and load variations. As a result, fault detection and isolation from rotor speed fluctuations are not reliable in the majority of practical situations.

In this section, we derive a new fault detection method on the basis of the parameter κ introduced in Section 3. By identifying changes in κ values, we can not only detect fault occurrence, but also identify the faulty phase and obtain the faulty current. In practical applications, it is important to know which phase is faulted. Knowing the faulty phase, one possible remedy action is to disconnect the faulty winding immediately to avoid the high shorty current from damaging other healthy windings. It is possible to control motors with only two stator windings, but this topic is beyond the scope of this paper. For fault detection, we assume that R, L, M, and λ_M are either known or estimated. Identification of κ is based on (3.7) $v = RIi - \kappa G_1 v_a + H\frac{di}{dt} - \kappa G_2 \frac{dv_a}{dt} + g$ and its discretized version (5.1).

(5.1) can be written equivalent in a regression expression as

$$z_k = \psi_k' \kappa \tag{9.1}$$

where z_k and ψ_k can be easily derived from (5.1). For computation of z_k and ψ_k, we point out that the inverse of H can be explicitly computed as

$$H^{-1} = \begin{bmatrix} \frac{L^2-M^2}{L^3-3M^2L+2M^3} & \frac{M^2-LM}{L^3-3M^2L+2M^3} & \frac{M^2-LM}{L^3-3M^2L+2M^3} \\ \frac{M^2-LM}{L^3-3M^2L+2M^3} & \frac{L^2-M^2}{L^3-3M^2L+2M^3} & \frac{M^2-LM}{L^3-3M^2L+2M^3} \\ \frac{M^2-LM}{L^3-3M^2L+2M^3} & \frac{M^2-LM}{L^3-3M^2L+2M^3} & \frac{L^2-M^2}{L^3-3M^2L+2M^3} \end{bmatrix}.$$

It is apparent that all previous algorithms remain viable, with y_k replaced by z_k and ϕ_k by ψ_k. As a result, we will not spell out the details here. To distinguish from the previous expressions, we will express the bias correction algorithm as

$$\kappa_N = \frac{\frac{1}{N}\widetilde{\Psi}'_N \widetilde{Z}_N - b}{\frac{1}{N}\widetilde{\Psi}'_N \widetilde{\Psi}_N - \xi}. \tag{9.2}$$

Note that the correction terms ξ and b are scalars, and the inverse is changed to a division here.

We first examine the bias from measurement noises. From the regressor expression in (9.1), the voltage measurement noises will cause estimation bias. We evaluate estimation biases on κ by applying i.i.d. Gaussian measurement noises of zero mean but different variances. σ_v is the standard deviation of the voltage measurement noise, and σ_i is the standard deviation of the current measurement noise. Table 2 illustrates estimation errors when noise variances increase. The sampling interval is 10 (ms), the estimation data length is 10000, $\mu = 0.5$ (50% inter-turn fault), $R_f = 10$, $L = 0.0064$, $M = -0.0021$, $R = 2.8750$. Apparently, the estimation biases are quite significant.

Table 2: Estimation Errors on κ without Bias Correction

σ_v	σ_i	True κ	Estimated κ
0.1	0.1	0.0233	0.0232
1	0.1	0.0233	0.0152
1	1.9	0.0233	0.0157

In comparison, if the bias-corrected estimation algorithm (9.2) is applied, the estimation accuracy can be significantly improved. This is shown in Table 3 under the same simulation conditions. Since the noises are i.i.d., $b = 0$. Hence, the bias correction is based on ξ.

Table 3: Estimation Errors on κ with Bias Correction

σ_v	σ_i	True κ	Estimated κ
0.1	0.1	0.0233	0.0234
1	0.1	0.0233	0.0232
1	1.9	0.0233	0.0241

9.3 Fast Fault Detection with Forgetting Factor

One critical requirement for fast fault detection is to make the identification algorithms rely more heavily on the recent data. As discussed in Section 7.10, this can be achieved by employing forgetting factors. Forgetting factor basically limits correlation between samples. If $\lambda = 1$ then least-square algorithm uses data with the same weighting factor regardless how far sample is measured from the current sample for which we need to decide what noiseless level should be. If $\lambda = 0$ least-square algorithm doesn't take and predecessor samples that they can influence current sampling value. In another words in that case we assume that all samples are independent and there is no influence between neighboring samples. There are several points regarding forgetting factor which we would like shed more

light on:

- how to compute λ based on noise level
- how λ influence estimation error

To illustrate the impact of forgetting factors on the speed of fault detection, we select different values of λ and show the responding trajectories of estimation algorithms in tracking κ after a fault occurrence in Fig. 29. It is clear that to achieve fast tracking capability, a small λ should be selected.

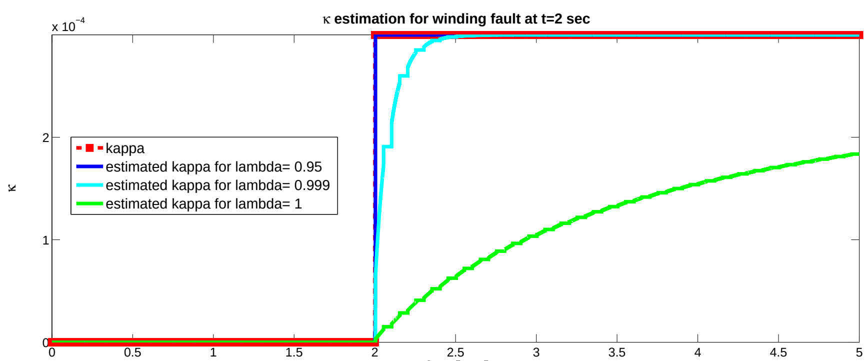


Figure 29: Estimation of κ for different λ

9.4 Case Studies on Fault Detection and Isolation

We now use several cases to demonstrate implementation and accuracy of the fault detection algorithm. The fault bypass has $R_f = 10\ K\Omega$. Fig. 30 shows the fault current which is very small (less than 1 mA). Also this fault is not visible in motor speed (RPM), as shown in Fig. 31. This implies that fault detection cannot be achieved by any methods that are solely based on motor speed measurements. In comparison, our algorithm can detect the fault promptly, see Fig. 32.

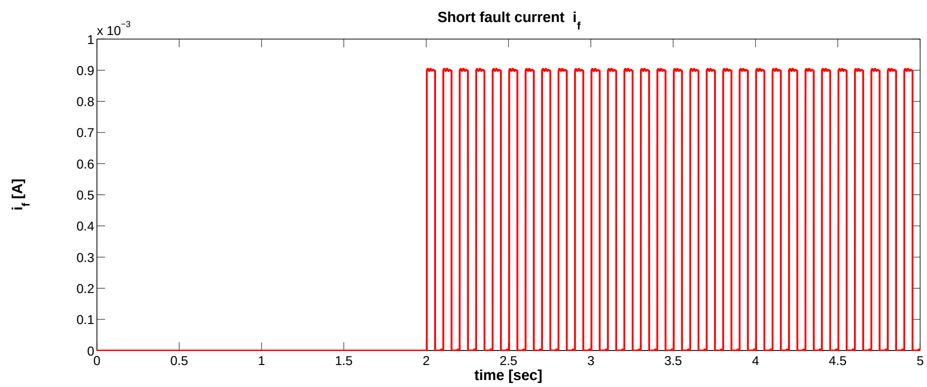


Figure 30: Short fault winding current if $R_f = 10$ K Ω

We proceed with identification of the faulty phase. Our fault isolation algorithm is based on estimating κ_a, κ_b and κ_c simultaneously. Since a winding fault in one phase will change its κ value and create an imbalance, this joint identification scheme allows us to use not only the κ value but also the variation in the symmetry to isolate fault. Here we present simulation results for a fault induced in Phase a at $t = 2$ second.

We now illustrate fault isolation by using the relationship between estimated κ_a and κ_b. In Fig. 33, the ratio $\frac{\kappa_a}{\kappa_b}$ is used as an indicator of imbalance. After a fault is detected, the

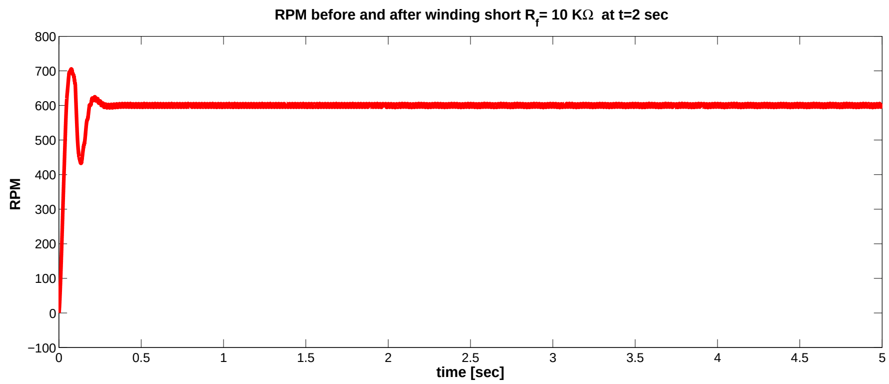


Figure 31: RPM of motor, fault acts at $t = 2$ sec and $R_f = 10$ KΩ

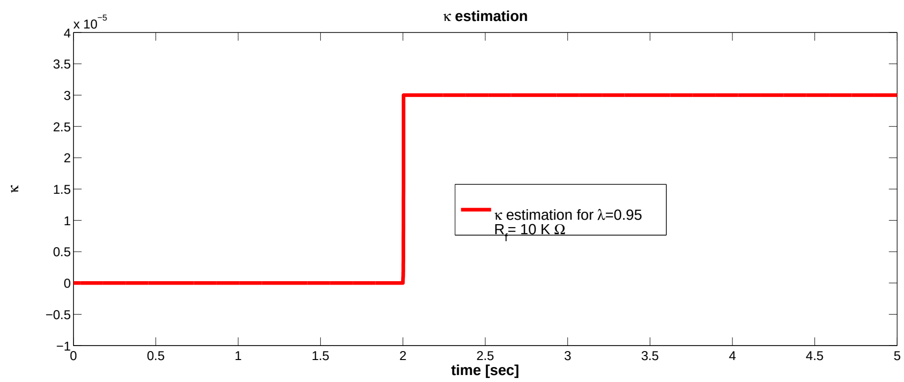


Figure 32: Fault detection for a fault at $t = 2$ sec and $R_f = 10$ KΩ

ratios of the pairs can be used as a simple criterion to determine which winding contains the fault. Fig. 33 shows that this ratio is highly effective in isolating the faulty phase from the others.

To demonstrate the importance of bias removal for fault detection, we present two case studies. The first one does not employ bias correction. Consequently, estimation accuracy may be lost. Fig. 34 clearly highlights that it is impossible to isolate the fault if estimation bias is not removed. As a comparison, Fig. 35 presents simulation results when the bias removal algorithm with forgetting factor is applied. In this case, fault detection and isolation

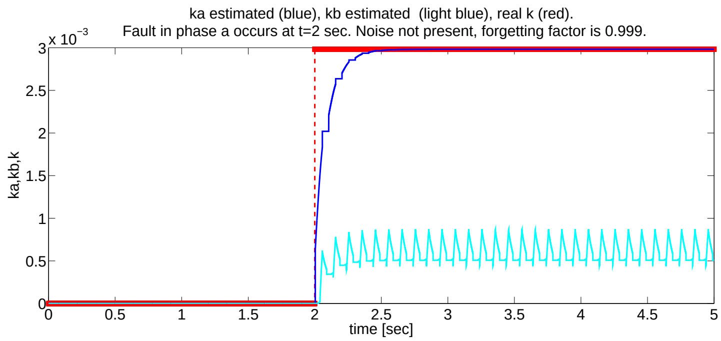


Figure 33: Fault in Phase a at $t = 2$ sec, κ_a and κ_b estimation, no noise

capability are restored, and once again the ratio of κ_a over κ_b becomes effective.

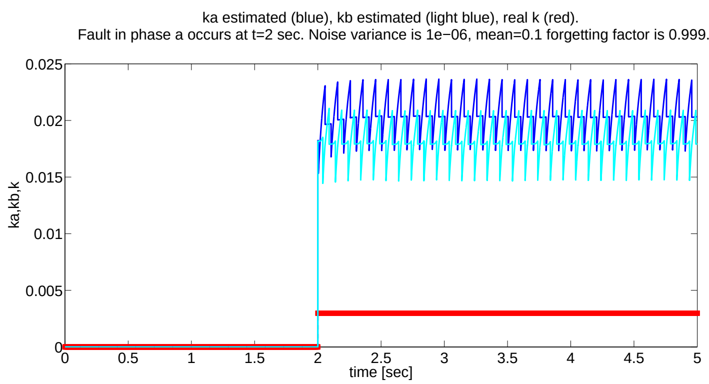


Figure 34: Fault in Phase a at $t = 2$ sec, κ_a and κ_b estimation, noise in all channels

9.5 Statistics for ξ and b

The bias correction algorithm (9.2) relies on the knowledge of ξ and b to devise correction actions. In practical applications, such covariance values may not be available *a priori*. As a result, they need to be estimated also. We now present an estimation scheme for ξ and b. For simplicity, we assume that all sensor noises are Gaussian i.i.d. random variables.

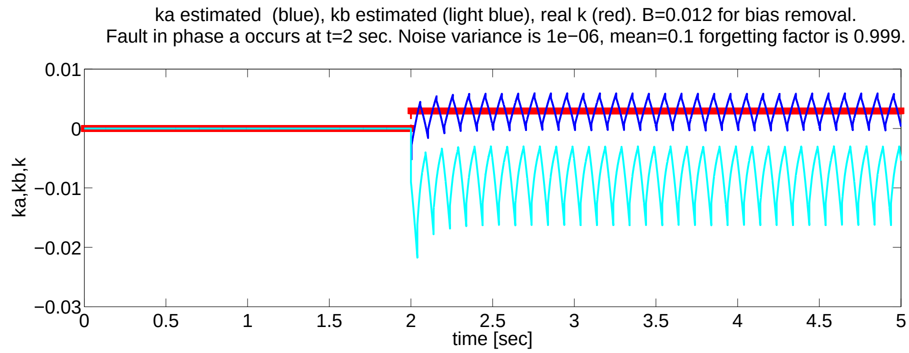


Figure 35: Fault in Phase a at $t = 2$ sec, noise present, bias removal applied

In our study, the motor starts without winding fault. This implies that at the starting time, $\kappa = 0$. Consequently, under normal operation, $Z_N = 0$. From the expression $\frac{1}{N}\Psi'_N Z_N \to A$, we conclude that $A = 0$ if $\kappa = 0$. From the equation $\frac{1}{N}\widetilde{\Psi}'_N \widetilde{Z}_N \to A + b$, we obtain $\frac{1}{N}\widetilde{\Psi}'_N \widetilde{Z}_N \to b$. This relationship can used for b determination when we know that no fault is present.

The identification equation for κ is $Z_N = \Psi_N \kappa$. We assume that the three-phase motor model is known. Hence Ψ_N is known. The measurement equations are $\widetilde{z}_k = z_k + e_k$; $\widetilde{i}_k = i_k + \varepsilon_k$. Substituting these equations in Ψ_N, we obtain $\widetilde{\Psi}_N = \Psi_N + \Delta_N$. The bias correction term is the limit $\frac{1}{N}\Delta'_N \Delta_N \to \xi$, which can be used to estimate ξ.

9.6 Fault Tolerant Motor Control

Permanent magnet and induction motor rotation is based on interaction between permanent magnets on the rotor and Tesla rotating stator magnetic field.

In the case of three phase permanent healthy motor we have all three phases operating.The three phase motor is given on Figure 36.

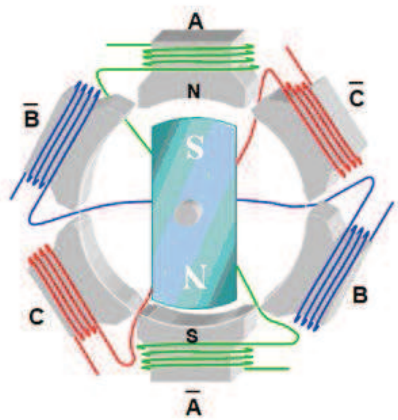


Figure 36: Two pole, three-phase permanent magnet motor

If fault is detected in one of stator phases that phase should be immediately disconnected because short may generates large amount of heat and to exponentially produce new shorts. Eventually the whole motor can burn in very short time.

Under fault tolerant motor control, in this thesis, it is assumed motor control which will allow motor with one phase disconnected to achieve all basic critical functions: start, deliver of minimally required power and torque during required time. In the case of vehicle that means that vehicle will be able to operate with reduced power even after winding fault occurrence. Therefore it is necessary to show how rotating magnetic field can be produced with stator having only two remaining phases. The word 'remaining' hints that these phases have the same space relation as in original three phase motor before fault. On the other hand operating motor with two phases is nothing new. Tesla motor had only two phases,but in Tesla case the winding´s axes were perpendicular, winding currents were sinusoidal and cosine alike (there were space and time lag between phases currents).

From linear algebra we know that any two non-collinear vector could be selected as a base for the plane in which these vectors are located. Also in vector space we assume that vector multiplication with scalar will produce a new vector. In the case of permanent magnet motor operating in 120 degrees regime (current is only ON during rotor sweeps 120 angle)that is not the case. In BLDC 120 case the same current flows through two windings and third current is always zero. Therefore magnetic field of these two currents are not independent. That is the reason why the special converter-inverter design is necessary, see Figure 1.

Here the method to obtain rotating field using only two phases will be given graphically. Of course the method is applicable even if we start with multi-phase motor (more than three phases). For simplicity three-phase motor will be used for explanation although the number of phases could be five, seven and so on. Let assume that phase C is disconnected due to winding fault. It will be graphicly shown that using A, B, -A, -B and its combination we can produce all six magnetic vectors necessary to generate standard rotating field, as we had with three windings and healthy motor.

From Figure 37 we see that we can produce all six vectors. Some of magnetic phasors are produced as resultant of existing currents though both windings A and B. In another cases single phase or inverted single phase current have been used.

Examples in 37 show how rotating field is generated in the case of BLDC motor when

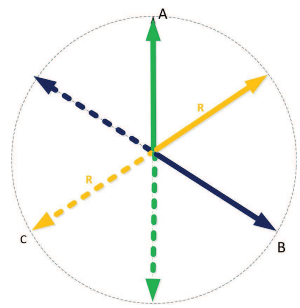


Figure 37: Six voltage generation with two phases: A and B

only two phases are conducting at the time. If fault happens and one of stator winding is deactivated then two remaining windings are sufficient to make rotating filed if the currents through remaining winding are mutually independent. In that case because two independent vectors span rotation plane then any vector in the plane can be generated and therefore required rotation vector can be generated. In literature first study about motor operating without one phase was published in [30]. In [13] experimental confirmation was presented. None of this papers discuss application to BLDC motor.

From now we assume that inverter is with four legs i.e that we can, if necessary disconnect faulty phase and to make each remaining phases magnetically independent. Let us consider two current coordinate systems S and SO. The first coordinate system S is original coordinate system in which currents are 120 degrees apart and where we have only two phases left. The SO is orthogonal coordinate system with the same coordinate origin. The control is going to be performed in orthogonal system. In that system we can compute what current change is required to achieve certain torque or speed. Once we know what orthogonal components of currents are required then by projecting these onto physical coordinate system we get reference physical values which will be produced. The required currents will be produced using

PWM. Therefore for control design we need invertible coordinate transformation between S and SO

$$\{S\} \rightleftarrows \{SO\}$$

This transformation must exist because both S and SO span the same space.

9.7 Fault prediction

The fault detection is good to have it. It would certainly be useful and convenient if we can predict winding fault event and, for example, replace the motor winding before fault happens. There are many stresses which cause winding fault fatigue and are potential causes of winding failure, see Figure 38, but in this thesis only the two of them which will be further studied: thermal and vibration/shock fatigue.

Motor Component Stresses				
Types of Stresses	Stator Winding	Rotor Assembly	Bearings	Shaft
Thermal	■	■	■	■
Electrical/Dielectric	■	■	■	
Mechanical	■	■	■	■
Dynamic		■	■	■
Shear				■
Vibration/Shock	■	■	■	■
Residual		■		■
Electromagnetic	■	■	■	■
Environmental	■	■	■	■

Figure 38: Electric motor stresses

9.8 Temperature as a cause of winding fault

Here we are going to propose new method for computing probability of winding failure. According to wire manufacturing reliability studies, see Figure 39 the probability of wiring insulation failure at certain winding point is proportional to total motor operating time and motor temperature at that point.

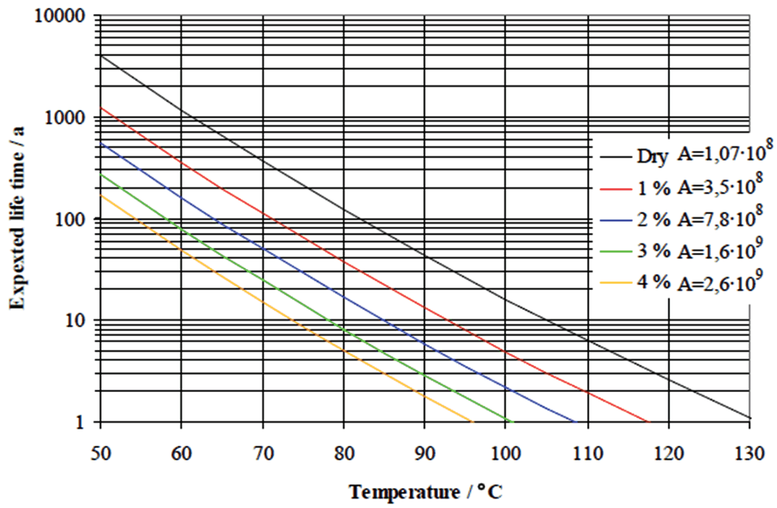


Figure 39: Winding life expectancy dependency on temperature

Clearly life expectancy curves could be used to estimate winding fault probability at time t and space coordinate x if operating motor temperature history, prior of t, is known for point x. So computed conditional probability could then be used in hypothesis testing both for fault prediction and fault detection. Two principles can be used to estimate motor winding temperature: inserting temperature sensors in the parts of winding with highest working temperature and observing that temperature or, using heat propagation motor model, which will allow us to to estimate winding temperature at point (t,x). The best thermal models are obtain using finite element approximation of heat transfer. In [73] an attempt is made to produce a low dimensional thermal model.

$$T = \begin{bmatrix} T_c & T_r \end{bmatrix}^T$$

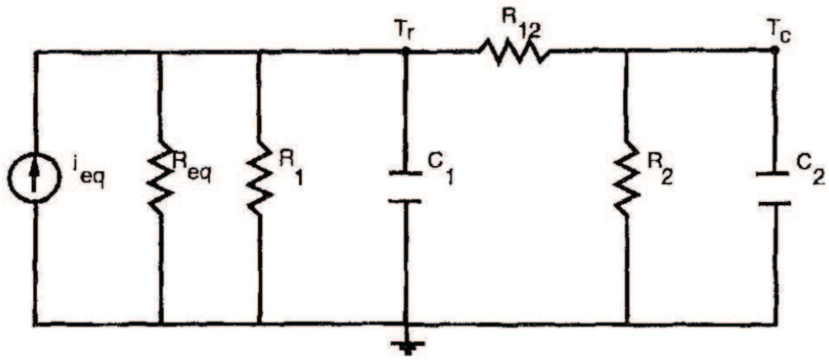


Figure 40: Lumped stator dynamic thermal model

$$\frac{dT}{dt} = AT + BT$$

Where A and B can be found using circuit method of independent voltages (in this case it will be independent temperatures).

9.9 Vibrations as a cause of winding fault

Vibrations fatigue is best estimated by installing an accelerometer on motor housing.

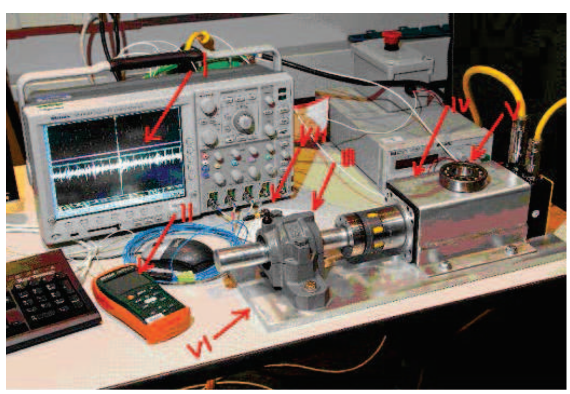


Figure 41: Vibration fatigue data collection

On this picture, in this order, we have Tektronix scope, thermocouple, bearing housing, servo motor, bearing, board and accelerometer.

CHAPTER 10: REAL-TIME DATA ACQUISITION

In this section data collection for proposed identification scheme validation will be given.

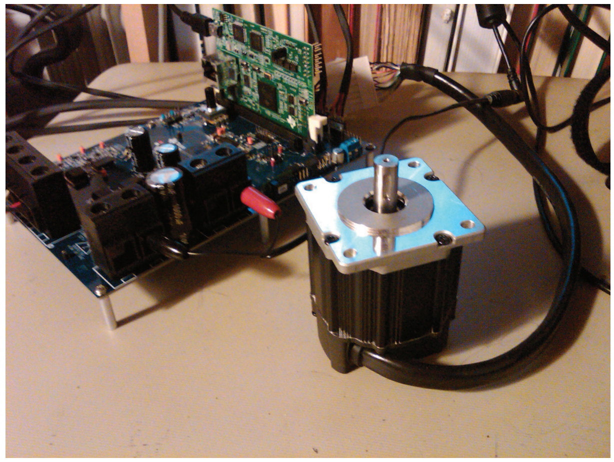
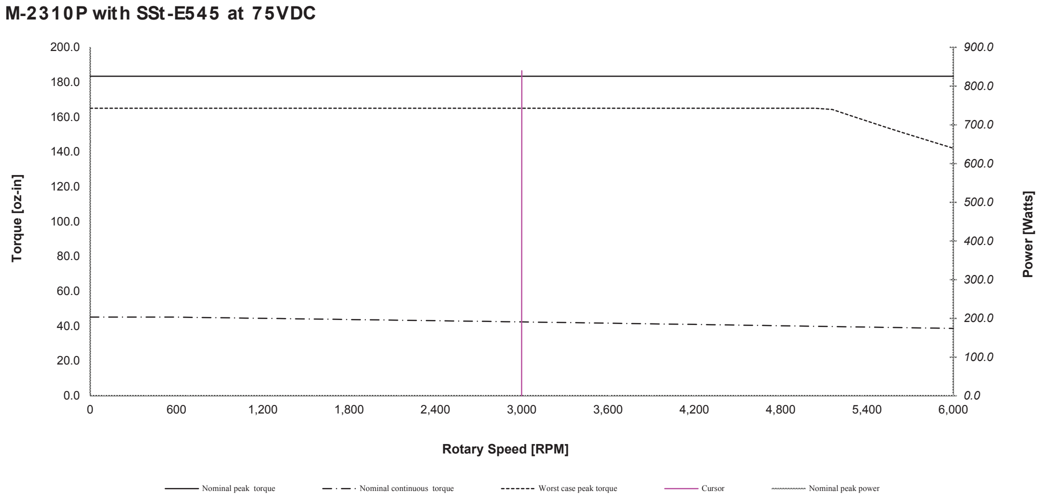


Figure 42: Teknic 700 W pm motor- Texas Instruments Hercules Kit

Figure 42 shows Texas Instrument Hercules Kit, DRV8301-LS31, used for data collection. The kit is composed from $700W$ motor, inverter and controller. For data collection two such motors were used where second motor was used for back-EMF data collection. In another words the second motor was used as generator. The configuration used for data collection is represented on Figure 44. On Figure 43 the characteristics, data sheet, of the motor is given. The data recording is composed from three input voltages, three phase currents and three back emfs. Figure 46 shows a phase voltage and Figure 47 a phase current. The Figure 48 shows zoomed contents of a phase current.



Peak Torque @ Cursor =	183.4	Cont. Torque @ Cursor =	42.4	Speed @ Cursor =	3000	
Ambient Temp (°C)	25.0	Ke (Vpeak/kRPM)	4.750	Nominal Peak Stall Trq. (oz-in)	183.0	
Winding Resistance @ Ambient (Ω)	0.717	Electrical Time Const. (mS)	0.561	Continous Stall Torque (oz-in)	45.1	
Inductance (mH)	0.402	Mechanical Time Const. (mS)	2.678	Wrst. Cs. Pk. Stall Trq. (oz-in)	165.0	
Drive Input Voltage (V)	75.0	Max Winding Temp (°C)	135	Nominal Peak Power (W)	814.1	(183 oz-in @ 6000 RPM)
Phase to Phase Peak Kt (oz-in/A)	6.419	Thermal Res.(°C/W)	2.170	Worst Case Peak Power (W)	631.5	(148 oz-in @ 5760 RPM)
Rotor Inertia (oz-in-s^2)	0.001	Resistance @ Tmax (Ω)	1.025	RMS Output Power (W)	171.7	
Static Friction (oz-in)	0.000	0 Ω Damping (oz-in/kRPM)	42.51	Drive Peak Current (A)	33.0	
Dynamic Friction (oz-in/kRPM)	0.000	"Black Watts" Limit (W)	10,000	Drive Cont. Current (A)	10.0	
RMS Torque Limit (oz-in)	53.961	Motor Constant (oz-in/W)	7.579	Motor Max Cont. Current (A)	8.12	Limted by the Motor

Printed: 2/23/2012 TS Calc, version 6.3 © 2011 Teknic Inc.

Figure 43: Teknic 700 W pm motor technical specification

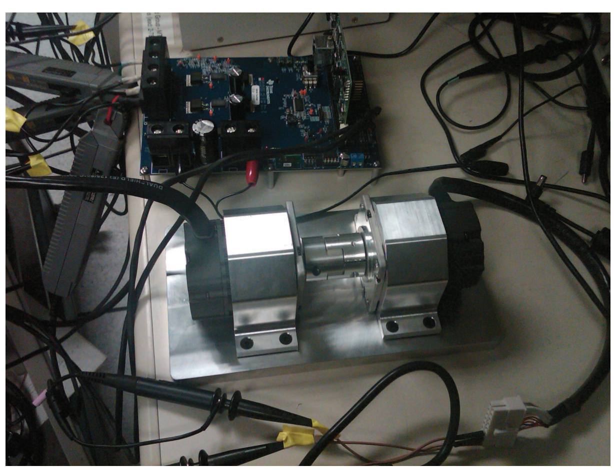


Figure 44: Two Teknic 700 W pm motors and Texas Hercules controller Kit

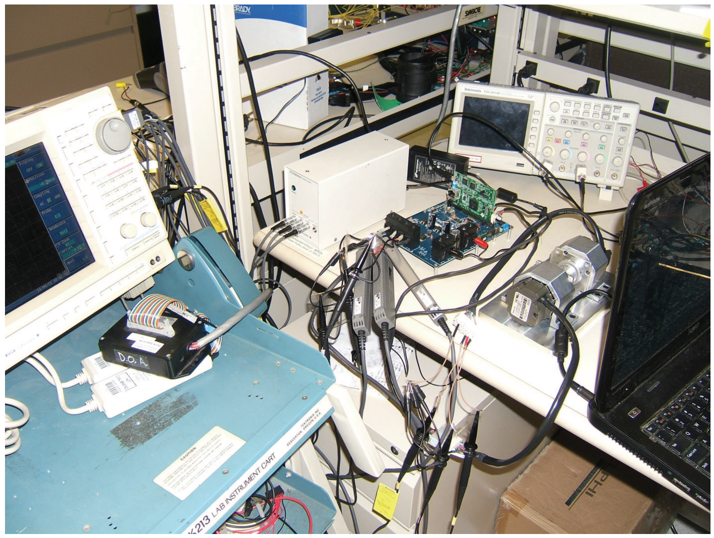


Figure 45: Data acquisition environment

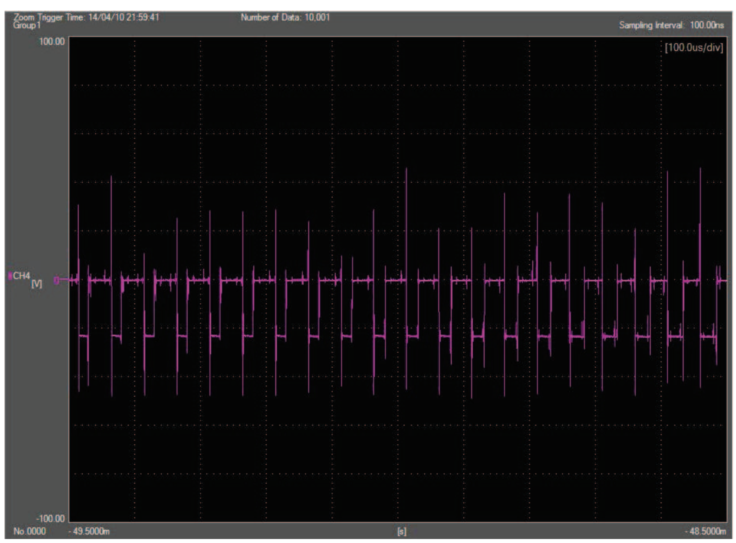


Figure 46: Phase voltage

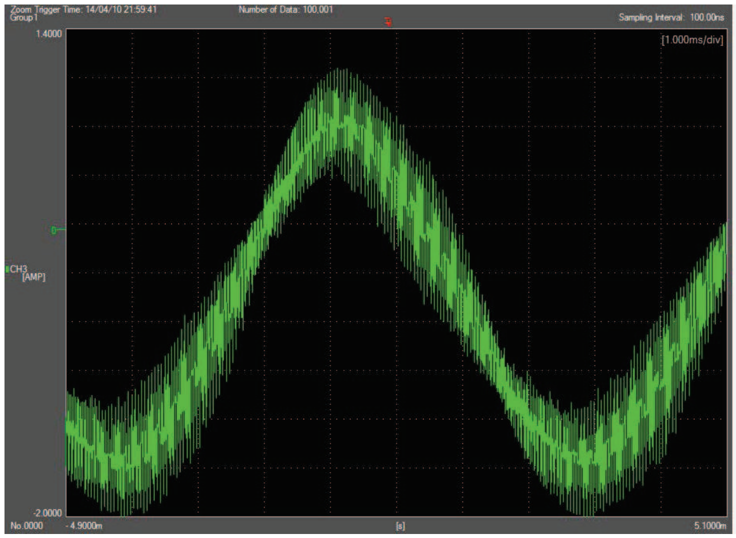


Figure 47: Phase current

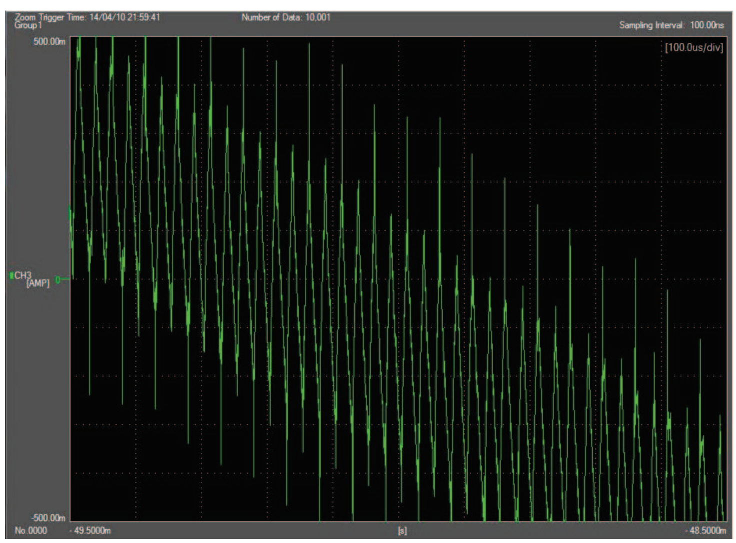


Figure 48: Phase current

CHAPTER 11: CONCLUSION AND FUTURE WORK

In this thesis application of robust real-time identification scheme for control and fault detection of electrical motors was considered. In particular least square method with bias removal was used for permanent magnet electrical motor parameter identification and winding fault detection. Although it was shown that proposed methods, through simulation and plant measurements, are successful there is a room for further improvements. The improvements can be made at least in next areas: more efficient inclusions of a priori knowledge into identification algorithm, reducing further influence of signal noise and statistics on identification efficiency and controlling influence of model-plant mismatch on identification results though filtering.

11.1 Robustifying Identification by a Priori Knowledge

In the early 1920´s R.A. Fisher (1890-1962) developed a new approach to statistical theory based on the idea that the object in calculating a statistic is to extract as much relevant information from the data as possible. To understand what could be the goals for further improving so far proposed identification approach it is necessary to first clearly define "relevant" terms because the solution to identification problem optimality depends of a priori posted goals. For example in a identification we can ask what is dynamics of variable X or if variable X is going to fall in certain interval before certain time. Note that in engineering, only relative to plant stability study, we allow for time to be indefinitely big or undefined. The asymptotic characteristics in other cases usually do not have engineering value. For example saying that estimation error will be close to zero after unknown time may mean nothing because in practice requirements for achieving goals are always expressed in certain finite time terms. The second question would be what are "data"? Very often under data we assume only measured samples and any other knowledge is considered as perturbation. So very often we propose identification problem algorithm and then we try to use other a priori available knowledge as constraint to solution of "free" identification problem. For example if we are trying to identify θ and we may know existence of bounds Θ_l, Θ_u such that

$$\Theta_l \leq \theta \leq \Theta_u$$

is valid all the time. Now the question is how to use this information to improve identification. If working with recursive least-squares procedures, one possibility would be to solve the identification problem without constraint and then to discard the solution if not in required bounds. The other option would be to use off-line iterative numerical methods for constraint problems but in many real-time applications that is not an option. So one of important topics to expend in future will be a design of recursive algorithm in the case when identified variable is a priori bounded by inequality constraints. It is logical to assume that algorithm should be based on recursive solution for the 'free identification problem' so in geometrical language constraint recursive solution should be projected onto constraint space. The expected result will be recursive least-square identification algorithm for constraint identification problem. Incorporating other types of a priori knowledge into identification problem formulation would be also beneficial. For example if constraint is given with linear equations these equations can be used to reduce identification space and so to simplify identification problem. Similar approaches for general types of constraints should be possible as well.

11.2 Improving Identification Robustness through Filtering

In general under robust identification, see for example [43], it is assumed that one sample will not have big influence on identification result. The other alternative would be to that observation which are different than rest of observation are coming from 'different' model i.e that some unknown factors were causing their behaviour and that for that reason we can make identification scheme robust if we make it sensitive to only events belonging to sets of measure different than zero (a single event). That requirement is easier to do in batch processing because we can go back and forth over data and so to determine which samples should be dropped out. In this thesis under 'robust identification' we assumed identification process as a multistage procedure and each of this components of identification procedures should be robust in its own sense. For example in this dissertation for identification algorithm the least-square method has been used even it is known that least-square has some advantages but also serious limitations. One major drawback of least-square method is that least-squares yields consistent estimation only if the error terms are asymptotically orthogonal to the regressors or, in the nonlinear case, to the derivatives of the regression functions. In the nonlinear case we do projection on the local osculating plane which is determined by derivatives at the working point. Consider, for simplicity, the linear regression model, [23],

$$y = \mathbf{A}\theta + u,\ u \sim \mathbf{IID}(\mathbf{0}, \sigma^{\mathbf{2}}\mathbf{I})$$

Here $\mathbf{A}$ is an matrix of explanatory variables. Regardless if u is correlated with $\mathbf{A}$ or not the residuals $\widehat{u}$ is orthogonal to $\mathbf{A}$. This means that, no matter how biased and inconsistent least square estimate may be, the least squares residuals will provide no evidence that there is a problem. Unfortunately there are many industrial cases when error terms are not orthogonal to matrix **A**. The most general technique for handling such situation, [23], is the method of instrumental variables (IV). The main difference between least-squares and instrumental variables method is using filtering, please see Figure 26. The study of incorporation filtering in least-square method as is done in Figure 26 versus presented least square method with bias removal would be beneficial. Useful parts of Total Squares could also be used to increase identification robustness as long as total identification method stays recursive and fast enough to be applied in real-time situations.

11.3 Non-parametric Identification Methods

Parametric model identification involves estimating the model parameters of a structural system from measured input - output data. In parametric inference we always postulate model order prior to identification and very often knowledge of noise distributions. In majority cases the model order is determined based on requirements and purpose of physical modeling. In some cases the practical understanding is that increasing model order will not help identification robustness because higher level modes will characterize not model but measuring noise. It is interesting to note that some authors argue that model order used for identification should be higher than real plant order, in order to absorb measuring noise and so to increase accuracy of identification process itself, [11]. In practice the model order is determined by control loop designer who may request that identification model order have to be under certain bound for given plant. In some areas of structural engineering the practice is to determine model order by estimating the rank of impulse response, i.e. Hankel matrix.

Algebraic approach in finding system order and using intentionally higher order model in order to increase accuracy of identification are interesting ideas and they should be studied in the future. Nevertheless, all parametric identification method assume that input - output noise density is of certain type, e.g. normal the most often. In late 60´s many cases were found where even small distance from normal distribution led to sharply wrong conclusions. It is also very close to truth to say that normal distribution is never found in practice. All that lead to study of non-parametric methods for identification. In this thesis some stages of proposed identification algorithm were based on non-parametric methods but that was possible due to permanent magnet model symmetry. In future it would be beneficial to see how the proposed method could be applied in the case of model non-linearity.

APPENDIX A: MOTOR CLASSIFICATION

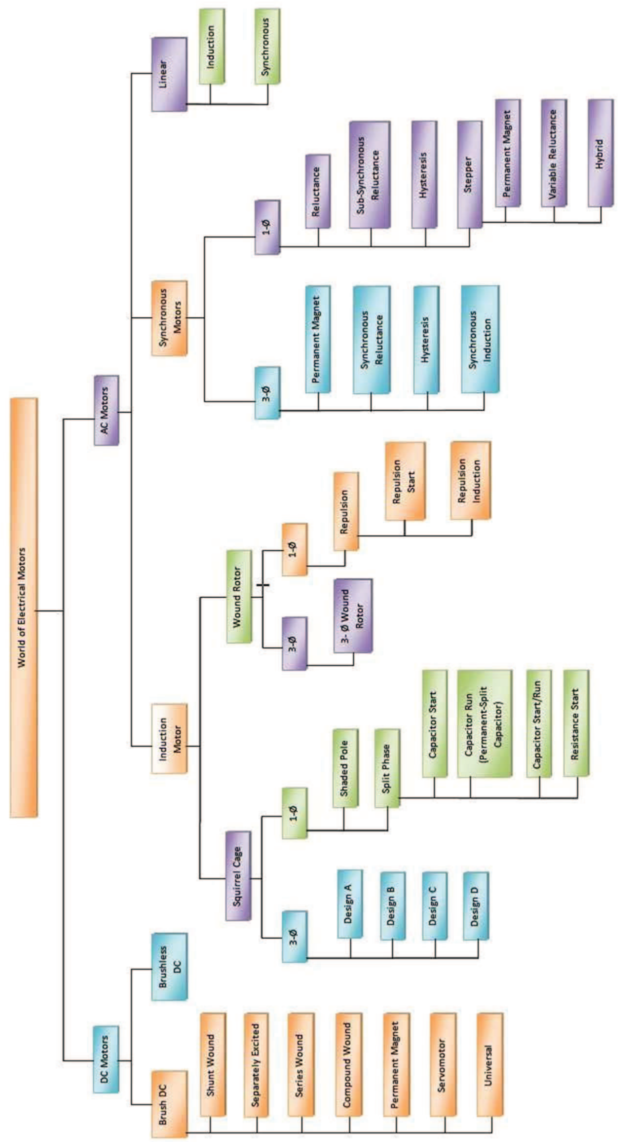


Figure 49: Motor Types

APPENDIX B: MOTOR WINDINGS AND PARTS

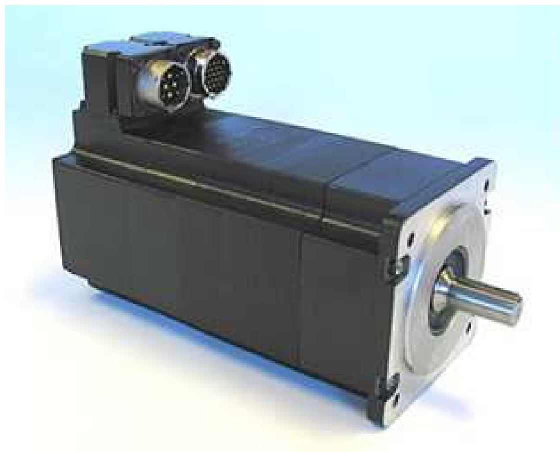


Figure 50: BLDC Motor

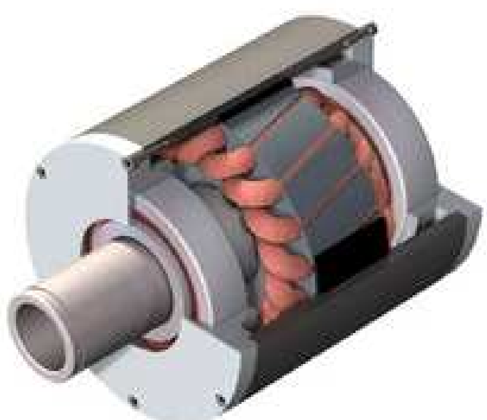


Figure 51: BLDC Internal View: Stator, Winding, Rotor

Figure 52: BLDC Motor: Stator Winding

Figure 53: BLDC traction motor

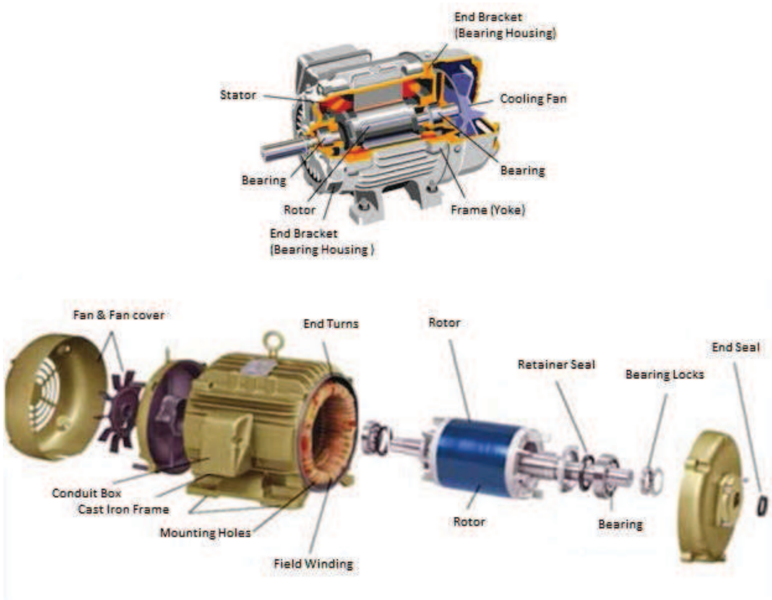


Figure 54: Induction Machine Cutway View

Figure 55: Fault tolerant stator winding

Figure 56: Four-pole surface mount PM rotor

Figure 57: DC-motor wound rotor

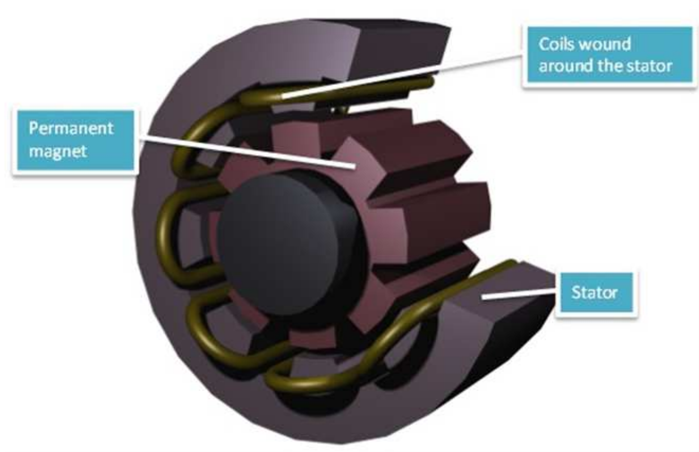


Figure 58: BLDC motor cross section

Figure 59: BLDC motor: rotor is taken out

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ABSTRACT

PARAMETER IDENTIFICATION AND FAULT DETECTION FOR RELIABLE CONTROL OF PERMANENT MAGNET MOTORS

by

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Advisor: Dr. Le Yi Wang

Major: Electrical and Computer Engineering

Degree: Doctor of Philosophy

Obtaining the dynamic behavior of motors during operation is of essential importance for control adaptation, condition monitoring, and diagnosis. Permanent magnet (PM) machines (sinusoidal and square current machines) are part of AC family of machines. High power density, high efficiency, small weight and high reliability are advantages of PM machines which makes them applicable for ground vehicle traction, and safety critical application. Todays drive are used in operations were faulty operation can cause loss of lives and high material cost. If steering wheel motor fails it will cause loss of control of a vehicle. If electrical pump fails in a nuclear station or on the airplane wing control it would be catastrophic. If gun steering mechanism fails on a tank during the battle the tank could be lost. In order to minimize damage to motor or generator the fault must to be detected as soon as possible and control scheme must be sufficiently adaptable that machine could perform some basic functions even in the presence of major fault.

The robustness of proposed continuous system identification and detection approach it has been validated through simulation.

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2. **Dusan Progovac**, Le Yi Wang, George Yin, "Bias reduction for reliable fault detection of electric motors under measurement noise of non-zero means", *Int. J. Modeling, Identification and Control*, to appear in 2014.

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1. **Dusan Progovac**, L.Y. Wang, G. Yin, "System identification for fault diagnosis of permanent magnet machines", *2013 IEEE Transportation Electrification Conference and Expo (ITEC2013)*, Detroit, MI, USA, 2013.

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